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The Social Impact of Natural Disasters : The Evidence from Japan

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URL	http://hdl.handle.net/10097/00128182

博士論文

THE SOCIAL IMPACT OF NATURAL DISASTERS: THE EVIDENCE FROM JAPAN

（自然災害から社会に与える影響−日本を例として−）

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ACKNOWLEDGEMENT

First, I would like to express my sincere gratitude to my advisor Prof. Yoshimichi Sato for introducing me to the field of sociology, for his continual support of my Ph.D. study and related research, and for his patience, motivation, and immense knowledge. Without generous support from his program, I could not have completed my Ph.D. degree. His guidance helped me in my research and writing of this thesis, and he is the best advisor and mentor for my Ph.D. study.

I would also like to thank the other members of my thesis committee: Prof. Kikuko Nagayoshi and Prof. Hiroshi Hamada. Prof. Kikuko Nagayoshi always proposed meaningful, detailed advice to advance my research. She provided me with the valuable opportunity to publish my first academic paper and helped me with the writing. Without their support, I could not have achieved my potential as a scholar. Prof. Hiroshi Hamada advised me on methodology, which strengthened my work, and critiqued the logic of my research, which helped advance my research.

My sincere thanks also go to my colleagues Prof. Daniel P, Aldrich, and Prof. Xiaonan Wang, who provided me an opportunity to coauthor with them. Prof. Daniel P Aldrich even offered me a distinctly vital opportunity to conduct research at Northeastern University. I have learned much from him, such as advanced writing skills and behaviors of successful scholars.

I would also like to thank my friends. I am thankful to Sun Gong and Akira Igarashi, for their helpful feedback on my work during the Ph.D. program. I also received generous financial support from the Japan Society for the Promotion of Science grants and the Inter-Graduate School Doctoral Degree in Science for Global Safety program.

The two datasets for this secondary analysis, Questionnaire Survey on Work and Hopes following the Earthquake and Survey on the Image of Foreign Countries and Current Topics, was provided by the Social Science Japan Data Archive, Center for Social Research and Data Archives, Institute of Social Science, and the University of Tokyo.

Last but not least, I would like to thank my family, especially my parents for their spiritual support throughout writing this thesis and my life in general.

ABSTRACT

This dissertation aims to examine how natural disasters impact behavior toward foreigners, income inequality, and opposition party support.

Specifically, Chapter 3 seeks to test the disaster impact on the behaviors toward foreigners empirically. Using an original prefecture-level panel data in Japan, this chapter investigates whether natural disasters have influences on the discrimination against foreigners. The fixed-effect model yields two main findings: (1) natural disasters have a short-term effect on decreasing discrimination; (2) this type of effect only existed in extreme disasters. These results provide supportive evidence for the common ingroup identity model after disasters.

Chapter 4 attempts to explore how and why natural disasters impact income inequality from a micro perspective. A survey data collated after the Great Eastern Japan Earthquake and tsunami is applied to investigate the disaster impact on individual income. Both the logistical and OLS regression model is used, and the results provide three main findings: (1) people who were non-regularly employed indeed were more likely to lose job in the disaster comparing with regularly employed workers; (2) however, because of the employment habit of labor market, non-regularly employed workers are less difficult to return to the same or even become to a higher employment status comparing with regularly employed workers; (3) throughout this approach, in the long term, non-regularly employed workers have smaller difference in current individual income, while regularly employed workers have bigger difference when comparing with nonaffected people. In a broader view, because people with lower socioeconomic status increased, the macrolevels inequality of individual income also increase after the disaster. These results provide evidence to prove disaster may promote income inequality from an individual perspective.

Chapter 5 attends to estimate how the disasters influence the supports of the opposition parties. The datasets at both individual levels collated after the Great Eastern Japan Earthquake and tsunami and original prefectural level panel data are used for the analyses. The multinomial logistic regression model at the individual level and fixed-effect model at the macrolevel are applied, and they have yielded two main findings. First, when the Democratic Party of Japan was the ruling party, people were less likely to punish it when affected by natural disasters, while when the Liberal Democratic Party was the ruling party, people were more likely to punish it. Second, people, at least in Japan, who were affected by the disasters, have a higher probability of supporting the parties that are more salient in managing economic growth and

welfare issues rather than supporting the challenger parties. The results provided the empirical evidence to the issue owner theory, which indicates that parties hold economic growth and welfare issues will be supported when these issues become salient.

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CHAPTER 1
Introduction: Background and Structure of This Study

Natural disasters are deemed "acts of God" (Black 1990), meaning that their occurrence is outside human control. As asserted by Alexander (1993, p4.), natural disasters are "quick-onset events with significant impacts on the natural environment upon the socioeconomic system". In this sense, natural disasters can cause significant damage to society. Natural disasters mainly cause casualties and economic damage directly. According to the World Disasters Report, summarized by the International Federation of Red Cross and Red Crescent Societies (IFRC) (2015), from 2005 to 2014, over 800 natural disasters occurred and caused approximately 830,000 deaths and USD 1,622,000 million in economic damage. Generally, population and economic growth are the main reasons for rising losses; however, in recent years, because of the acceleration of global warming, extreme natural disasters are increasing rapidly and causing more casualties and financial losses (Botzen, Deschenes, and Sanders 2019).

Indirect impacts, assessed as the aftermath of disasters, also have a significant effect on society (Lindell 2011). The first social scientific study of a disaster was by Rousseau, who attempted to observe the effect of the 1755 Lisbon Earthquake on residents' evacuation (Dynes 2000). From then on, the following pioneer studies in this field started to treat disasters as the opportunity to investigate the collective behavior under extreme conditions (Quarantelli 1987). In recent research, according to Lindell (2011), the social impacts of natural disasters have been divided into three aspects: psychosocial impacts, economic impacts, and political impacts.

Psychosocial impacts refer to social behavior changes caused by natural disasters (Tierney 2007). Early publications focused on demonstrating social behaviors during or after disasters such as enhanced community connections, declines in crime and other antisocial behaviors, and the development of therapeutic communities (Fritz 1961; Barton 1969; Dynes 1970; Quarantelli and Dynes 1972). Additionally, researchers have systematically provided the empirical evidence that enabled this pioneering research by using collected datasets (e.g., Barton 1969; Calo-Blanco et al. 2017; Chang 2010; Fritz 1961; Lee and Freser 2019; Prelog 2016; Solnit 2009). However, these researchers focused on the effect of disaster impact on attitudes and behaviors by treating society as one group.

Obviously, many types of groups live in a society, and they have attitudes and behaviors toward each other, but how disasters impact intergroup behavior remains unknown. The literature has indicated that the positive behavior of a whole society may only exist within ingroups, and to people from outgroups such as foreigners, these types of behaviors may be perceived as negative and exclusive (Green and Cooper 2015; Jha 2015). Studies have suggested that disasters may be an impetus for a better society, such as the aforementioned enhanced community connections (Fritz 1961; Barton 1969; Dynes 1970; Quarantelli and Dynes 1972). However, if the attitudes and behaviors among groups become negative after disasters, that evidence would contradict the evidence in the literature. Moreover, because of globalization, immigration is more frequent, and foreigners become a critical part of society. In this sense, managing the relationship between natives and foreigners, especially after disasters, is crucial for the government. In these contexts, understanding the behaviors of natives and foreigners is necessary.

Economic impacts include property damage and changes in wealth distribution (Lindell 2011). A study suggested that disasters expand the inequality of individual-possessed wealth, such as "checking and savings accounts, real estate holdings, vehicles, farms, businesses, stocks, annuities, and other savings" (Howell and Elliott 2018: p.5). However, this study did not include individual income in the measurement of possessed wealth. Income differs from possessed wealth or property because it depends on individuals' employment and is property not already possessed. Disasters can only influence one's income indirectly through effects on their employment, compared with the direct influence on possessed wealth. Therefore, the impact of disasters on individuals' income differs from possessed wealth.

Regarding the influence of disasters on income inequality, most researchers have argued that it would increase after disasters (Fang et al. 2017; Guimaraes et al. 1993 Shaughnessy et al. 2010), whereas other researchers have indicated that disasters would decrease income inequality (Abdullah et al. 2016; Feng, Lu and Wang 2016; Keerthiratne and Tol 2018). The results in the literature are inconsistent, which may be caused by the level of analyses. All these researchers have conducted only macrolevel analyses; however, other factors at the macrolevel also caused by disasters may simultaneously affect income inequality. These factors cannot be avoided only through the analyses at the macrolevel. For instance, after disasters, some governments provide disaster aid to victims (Feng et al. 2016). This policy may decrease income inequality in disaster-affected areas. However, in cases where the government provides no disaster aid, income inequality may increase after disasters. The different results in the literature may be caused by these types of macrolevel factors. Thus, to avoid this disadvantage, analyses at the microlevel are necessary.

Furthermore, in the literature that has focused on analyses at the macrolevel, although the mechanisms they mentioned were all at the micro or individual level. This method is inappropriate because macrolevel data cannot avoid factors that may simultaneously influence income inequality. For instance, after disasters, population mobility becomes frequent (Elliott and Howell 2017; Landry et al. 2007), and people with lower socioeconomic status are more likely to move out of the affected areas. Therefore, the decline of income inequality may only be caused by population mobility and not the mechanisms assumed in the literature. The analyses at macro-level cannot decide whether the influence is caused by population mobility or mechanisms assumed only through macrolevel data. In this sense, the use of individual-level data is necessary to demonstrate the mechanisms of disasters that promote or reduce income inequality.

Political impacts refer to social activism resulting in political disruption (Lindell 2011). Studies, especially studies in the United States' (US) social context, have concentrated on the punishment of the citizens by the incumbent government or party, and most have found that after natural disasters, people punish incumbent governments or parties (Cole et al. 2012; Gasper and Reeves 2011; Healy and Malhotra 2009, 2010). Furthermore, several researchers have noted that people would dismiss the incumbent party in support of the opposition party if the incumbent party inappropriately managed a disaster (Cavallo and Noy 2010; Chang and Berdiev 2015; Keefer et al. 2011; Vaugirard 2007). However, no studies have attempted to empirically demonstrate how disasters affect the support of opposition parties. In the US social context, two parties are the ruling parties, and the voters decide their degree of power in governance; therefore, disasters decrease support for the incumbent party and promote support of the opposition party. Compared with the two-party system in the US, most countries use a multiparty system, that is, a "regime where more than two political parties are in serious contention for power, alone or in coalition" (McLean and McMillan 2009: p: 46); thus, compared with the US, what type of opposition party is more likely to be supported after disasters in these countries remains unknown. Because disasters increase the likelihood of governmental replacement (Chang and Berdiev 2015), predicting the next ruling party is a crucial problem for laypeople and scholars. Therefore, an estimation of which opposition party is more likely to be supported after disasters is necessary.

According to the aforementioned information presented in the introduction, all the literature on the impacts of natural disasters on the three dimensions of societies have disadvantages, and these disadvantages are all crucial to academic and governmental aspects. Therefore, in managing these disadvantages, this study attempts to explore the impact of natural disasters on behaviors toward foreigners, income inequality, and opposition party supports by using Japan as an example.

Japan is an appropriate example for testing these demonstrations. First, Japan is the country affected by natural disasters, for example, typhoons, heavy snow, earthquakes, tsunamis, and volcanic eruptions. These disasters influence Japanese society, especially large-scale disasters. Thus, an exploration of how natural disasters impact Japanese society is necessary. Second, because Japan has no major minority groups, such as the Asian American population in the US, the central majority and minority groups are the Japanese and foreigners. These demographics make drawing conclusions on the attitudes and behaviors toward foreigners impacted by the natural disasters in Japan easier. Finally, Japan is a democracy with a multiparty system; thus, we can explore how disasters impact the support of opposition parties.

The structure of this study is as follows. At first, Chapter 2 presents a more detailed review of the literature. Then, the remaining three chapters present the empirical demonstrations: (1) using the panel data at the prefecture level of Japan, Chapter 3 investigates whether disasters increase or decrease discrimination by Japanese people against foreigners; (2) relying on the data at individual level, collected after the Great Eastern Japan Earthquake, an unpredictable and the biggest disaster in Japan since 1995, Chapter 4 estimates whether disasters increase or decrease income inequality at individual level; (3) utilizing both individual-level data collected after the Great Eastern Japan Earthquake and prefecture-level panel data, Chapter 5 explores how disasters influence the support of opposition parties, and which party is more likely to be the next ruling party after disasters. The structure of this study is shown in Figure 1.1.

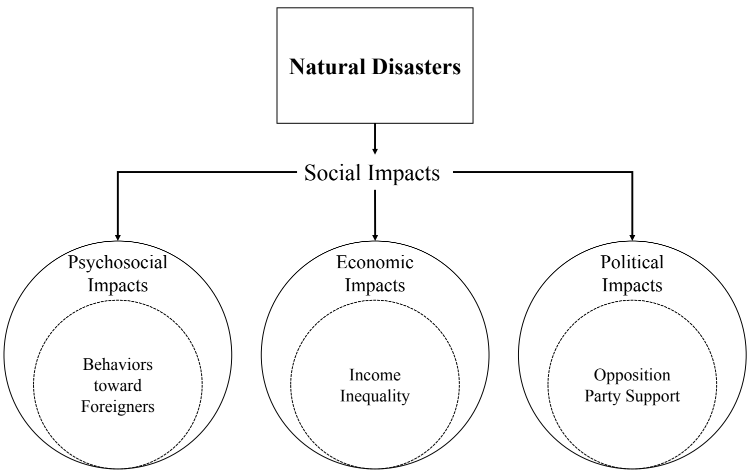

Figure 1.1 Study Content

The results show the following: (1) natural disasters decrease rather than increase discrimination against foreigners; however, this decrease is observed only in large-scale disasters and in the short term; (2) natural disasters promote income inequality through influencing individuals' employing replacement; (3) natural disasters only promote support for parties with salient concerns about economic growth and welfare. This study contributes to the literature by filling the gaps concerning the impacts of natural disasters on society. The implications of the results are discussed in Chapter 6.

CHAPTER 2
Literature Review: Impact of Natural Disasters on Behaviors toward Foreigners, Income Inequality, and Opposition Party Support

2.1 Behaviors toward Foreigners

Disaster studies of the US have summarized that minority racial groups, such as African Americans and Latinos, are the most vulnerable groups before, during, and after disasters (Fothergill et al. 1999). This phenomenon occurs because these groups generally have low socioeconomic status (American Friends Service Committee 1972; Bolin 1993, 2007). Foreigners are also a type of vulnerable group both during and after disasters because of language barriers rather than socioeconomic status (Kawasaki et al. 2018). Another way that foreigners are exposed as a vulnerable group after disasters is the negative behavior toward them from native people.

Studies have demonstrated that native people affected by disasters are less likely to provide help to foreigners than to native people (Andrighetto et al. 2015) and that the mechanism of this finding could be interpreted as the intergroup threat theory (Stephan and Stephan 2000; Stephan et al. 2009), especially the realistic threat theory (Andrighetto et al. 2015). Realistic threats are "…threats to the very existence of the ingroup, threats to the political and economic power of the ingroup, and threats to the physical or material well-being of the ingroup or its members" (Stephan and Stephan 2000: 25). Indeed, disasters cause the social loss, which could lead the ingroup to treat outgroup as a threat to obtaining resources. Group conflict theory mentions that the negative attitudes and behaviors between groups will be promoted by competition for limited resources (LeVine and Cambell 1972; Sherif 1966); thus, the disasters or perceived disaster damage of individuals may promote negative attitudes and behaviors toward the outgroup.

Two incidents provide satisfactory examples of this theory. The first example is the Kantō Massacre (Aldrich 2012). After the 1923 Great Kantō Earthquake, anti-Korean riots occurred, and many Koreans were killed based on a rumor that Koreans would poison the wells. This catastrophe reflects the increasing discrimination of Japanese people toward other nationalities. The second example occurred recently in Japan (The Japan Times 2018). After the 2018 Osaka Earthquake, "scores of tweets were observed that labeled ethnic non-Japanese, particularly ethnic Koreans and Chinese, as criminals who may take advantage of post-quake confusion to loot banks and convenience stores, and commit other dangerous crimes" (The Japan Times 2018).

Because this incident aimed to the foreigners, it could be counted as the present of discrimination against foreigners.

By contrast, other theories imply that positive attitudes and behaviors toward outgroups are also possible during or after disasters. Studies have provided the common ingroup identity model (Gaertner and Dovidio 2000, 2012) to explain the altruistic behaviors between two different groups. The aforementioned intergroup threat theory is based on the remaining social identity that native people still categorize themselves as the ingroup compared with foreigners who are treated an outgroup. The social identity theory mentions that people improve their self-identity through membership in prestigious social groups (Tajfel and Turner 1979). Therefore, this self-identity causes social comparisons to distinguish the ingroup and outgroup. Furthermore, the self-categorization theory generalizes this theory of intergroup and intragroup processes and emphasizes cognitive processes (Turner et al. 1989). However, according to the common ingroup identity model, people affected by an external threat such as a terrorist attack (Dovidio et al. 2004) or earthquake (Vezzali et al. 2015) decategorize themselves as a member of the ingroup and become personalized to cooperate with other people from outgroup (Gaertner and Dovidio 2000, 2012). Furthermore, according to the contact hypothesis (Miller and Brewer 1984), this cooperation will disrupt the bias and improve the positive attitudes between the ingroup and outgroup, leading to fewer negative behaviors such as discrimination toward people from the outgroup. Consequently, through this mechanism, the disasters may improve positive attitudes and reduce discrimination toward the outgroup.

Evidence of this theory has been presented by several researchers. In the psychology literature, students have been the experimental target to explore whether the native students help students from outgroups during disasters or crises (Dovidio et al. 2004; Vezzali et al. 2015). They found that native students affected more by a crisis are more likely to provide help to students from outgroups. In addition, according to Takezawa (2007), in the Hanshin-Awaji Earthquake, the local Japanese residents in the affected areas treated the foreigners as the same group. This phenomenon also demonstrates that people affected by the disaster from both the ingroup and outgroup will treat each other without the categorization.

Regarding these two contrary theories, although the literature has presented several cases and experiments to support them, the evidence is insufficient to prove whether natural disasters promote or reduce discrimination against foreigners. The aforementioned cases are inconsistent within the same society—Japan (Aldrich 2012; Takezawa 2007; The Japan Times 2018). Thus, determining the theory through these several cases is difficult. The experiments provided by psychologists have only focused on students (Dovidio et al. 2004; Vezzali et al. 2015). As aforementioned, native people discriminate against foreigners mainly because of the economic threat (Stephan and Stephan 2000; Stephan et al. 2009). Because students have no independent socioeconomic status, they are less likely to feel the economic threat from foreign students. Therefore, they tend to help foreign students in a crisis. However, the general situation of the whole society is unknown on the basis of these experiments, and further research is necessary to conduct a more comprehensive empirical demonstration to prove whether natural disasters promote or reduce discrimination against foreigners.

2.2 Income Inequality

Social vulnerability theory has indicated that natural disasters have a greater impact on poor agents (Alexander 2012; Cutter 2003; Fothergill and Peek 2004). Risk theory also suggests that the risk of disasters is concentrated in the lower classes (Breen 1997). The empirical studies have also provided the evidence for these theories (e.g., Kuznets 1955; Kawachi et al. 1997).

Regarding income inequality, the literature has also suggested that it expands after natural disasters (Fang, Wu, and Milijkovic 2017; Milijkovic and Milijkovic 2014; Yamamura 2015). However, few researchers have mentioned the mechanisms for why disasters increase income inequality. Following social vulnerability theory, Yamamura (2015) proposed a mechanism to explain this influence: poor people are more likely to be affected by disasters because they work in informal sectors, and rich people work in formal sectors. Informal sectors are less likely than formal sectors to ensure continuous operations after disasters; therefore, rich people can continue to earn money after disasters, whereas poor people become unemployed or are less likely to go back to work. Consequently, income inequality may increase after disasters.

Contrasting evidence has also demonstrated that natural disasters may decrease income inequality. Abdullah et al (2016) found that higher-income households were more vulnerable in a disaster because the damage costs for higher class were 42%, and this cost for middle and lower class was 16% and 15%, respectively. Consistent with this study, research on the Wenchuan Earthquake in China found that income inequality decreased after the disaster mainly because of the government aid (Feng et al. 2016). Likewise, in Sri Lanka, Keerthiratne and Tol (2018) found that income inequality, measured by the Gini coefficient, decreased after natural disasters. The mechanism that explains why disasters reduce income inequality was proposed by Keerthiratne and Tol (2018) and mentions that losses for people with higher socioeconomic status would be disproportionately greater because of natural disasters.

Studies that have explored the influence of disasters on income inequality have provided inconsistent results, and the reason for this consequence may be their use of macrolevel analyses. However, other macrolevel factors also caused by disasters may simultaneously affect income inequality and are avoided only through macrolevel analyses. For instance, after disasters, some governments provide disaster aid to the victims (Feng et al. 2016). This policy may help decrease income inequality in disaster-affected areas. However, when governments provide no disaster aid, income inequality may increase after disasters. The different results in the literature may be caused by these types of macrolevel factors. To avoid this disadvantage, analyses at the microlevel are necessary.

Moreover, the analyses conducted in literature have been at the macrolevel, but the mechanisms applied were at the microlevel. This method is inappropriate because macrolevel analyses provide an inaccurate demonstration of the mechanisms, that is, factors at macrolevel caused by the disasters may simultaneously affect income inequality. For instance, after disasters, population mobility increases in frequency (Elliott and Howell 2017; Landry et al. 2007), especially for people with lower socioeconomic status, who are more likely to move out of the affected areas. Therefore, the cause for the decline in income inequality may be population mobility rather than the mechanisms assumed in the literature; thus, whether the influence is caused by population mobility or the mechanisms remains unknown because an assumption is made based on only macrolevel data. Similarly, in this sense, individual-level data must be used to demonstrate the mechanisms that explain why disasters promote or reduce income inequality.

Estimations of whether disasters expand income inequality at the individual level must focus on employment status because income is mainly from wages. As aforementioned, people with lower socioeconomic status are more likely to lose jobs than people with a higher socioeconomic status (Elliott and Pais 2006; Yamamura 2015). People with lower socioeconomic status are also more likely to have non-regular employment or be unemployed compared with their higher socioeconomic counterparts; notably, regular employment status is an index for measuring socioeconomic status. In this sense, people who engage in non-regular employment or who are unemployed are more likely to lose jobs compared with people who have regular employment.

The employment of unemployed individuals is not affected by disasters; therefore, their cases are inconsistent with the mechanism that disasters influence individuals' income through the effect on their jobs. Accordingly, in this study, to purely explore the mechanism at the individual level, people unemployed before the disaster are excluded.

For non-regularly employed workers, in the short term, social vulnerability theory, which suggests that people with lower socioeconomic status are affected more in the disasters, may be correct; however, in the long term, it remains unknown. After disasters, people who lose their job must seek a new job to obtain the income required to sustain their life. Generally, non-regular employment is easier to obtain compared with regular employment because the former decreases labor costs for employers. Therefore, people engaged in non-regular employment before disasters can more easily return to their employment status after disasters compared with people engaged in regular employment before disasters, who may have difficulty returning to their employment status after disasters; thus, of the two groups, the regular employment group would be more likely to lose their employment status and become non-regularly employed or unemployed. Therefore, people engaged in non-regular employment before disasters may have the same or only a slightly lower level of income than before disasters, whereas people engaged in regular employment will have a much lower level of income than before disasters because regular employment provides a higher level of income than non-regular employment.

From this point of view, at the individual level, people who had a higher level of income before disasters drop to lower-income levels, and people who had lower incomes maintain their status. In this situation, although the total income difference between workers who were regularly and non-regularly employed will decrease after disasters, when expanding the view to the whole society, total income inequality will increase because the income of people with a lower socioeconomic status increased. Thus, for assessments of the impact of disasters on income inequality, empirical analyses should be conducted at the individual level.

2.3 Opposition Party Support

As mentioned in Chapter 1, natural disasters are deemed “acts of God” (Black 1990) because these events are beyond human control. Additionally, natural disasters are sometimes deemed “bad omens for governments” because they can change government stability (Abney and Hill 1966: 974). Studies have indicated that natural disasters alter politics by offering unexpected trial of governance for the incumbent parties (Gasper and Reeves 2011). In early studies, for instance, Barnhart (1925) indicated that drought decreased the voting share of Nebraska’s Republican Party in the 1890 election in the US. The research subsequent to that study started to explore the effect of natural disasters on the support, especially the voting share, for the incumbent party or government (e.g., Achen and Bartels 2013; Gasper and Reeves 2011; Healy and Malhatra 2009, 2010; Healy et al. 2010).

This type of punishment for the incumbent party is summarized as *retrospective voting* (e.g., Kramer 1971; Fiorina 1981). Furthermore, other studies have indicated that people tend to punish the incumbent party because these voters are instrumentally rational (Hernández and Kriesi 2016), that is, they reward or punish incumbents with their vote when they perceive a situation is good or bad, respectively. Gasper and Reeves (2011) divided electorates into two types: responsive and attentive. Responsive electorates "punish the incumbent party based on the state of the world without regard for the responsibility of the incumbent in shaping it" (Gasper and Reeves 2011: p.341). In other words, responsive electorates punish the incumbent party after disasters, without considering the policies the party implemented before, during, and after the disaster.

Attentive electorates are attentive to "the actions of their elected officials and assign blame based on the authority and actions of the incumbent party" (Gasper and Reeves 2011: p.342). In other words, the punishment of voters after disasters depends on the actions taken by the incumbent party. Some researchers have found that if the incumbent party announces a declaration of the disaster immediately after the disaster, she or he will not be punished by the voters (Cole Healy and Werker 2012; Gasper and Reeves 2011). However, as mentioned by Healy and Malhotra (2009), voters are more likely to punish or reward incumbents according to the policies published after the disasters; by contrast, if disaster policies are published before disasters, voters do not tend to evaluate incumbents, even though the policies have a higher probability of protecting the voters against the negative effects of disasters. Healy and Malhotra (2009) call these voters *myopic voters*.

Studies have estimated whether and how citizens punish the incumbent party after disasters. The opposition parties tend to treat the punishment as an opportunity to assess blame (Quarantelli and Dynes 1976). Part of the literature has even noted that citizens might dismiss the incumbent party in support of the opposition party if the incumbent party did not manage the disasters appropriately (Cavallo and Noy 2010; Chang and Berdiev 2015; Keefer et al. 2011; Vaugirard 2007). Additionally, as indicated by Chang et al. (2015), natural disasters could also increase the probability of governmental replacement; thus, predicting the next ruling party becomes a crucial issue for the citizens after disasters. In the US social context, a two-party system, when the incumbent party is punished by the voters, the opposition party will surely gain support. However, when the social context is a multiparty system, predicting which party will benefit from the disasters is difficult without research. Therefore, how to predict which opposition party is more likely to be supported after disasters is crucial.

Concerning this question of how, according to the literature, two types of theories can lead to two adverse results of a disaster's impact on the support for opposition parties. The first adverse result is based on economic voting theory. According to studies on economic crises, economic crises have been suggested to increase support for the emerged-challenger parties (Bosch and Durán 2019; Hobolt and Tilley 2016). The reason in this case can also be explained by economic voting theory. Voters will "throw out the rascals (Hobolt and Tilley 2016: p. 972)" according to the poor economy. The "rascals" include not only the parties in the government but the mainstream parties in opposition because they have also been involved in formulating the economic policies. Voters are unsatisfied with the existing political situation and want to support a new political party that provides policies that differ from the government and mainstream parties. Thus, the challenger parties will provide policies that conform more to the voters' expectations to obtain a greater voting share. In this situation, the voters support the challenger parties. For instance, recently, because of economic depression and an increased number of refugees, most people in European countries have voted for and elected challenger parties, such as Alternative (Germany), the Five Star Movement (Italy), and Podemos (Spain) (Hobolt and Tilley 2016). According to the general demonstration, the literature also found that economic crises increase support for challenger parties (Bosch and Durán 2019; Hobolt and Tilley 2016). In this sense, voters are more likely to support challenger parties after a crisis.

Natural disasters affect society because they cause poor economic performance, such as a lower unemployment rate, and property damage; thus, economic voting theory is likewise appropriate to apply in cases of natural disasters, that is, natural disasters may promote support for challenger parties. Because challenger parties are newly emerged, they have no experience in governance before being elected as the ruling party. Thus, although they propose policies to manage the crisis, people do not know their real ability to resolve problems. Compared with economic voting theory, ownership theory provides another possibility for opposition party support after disasters.

According to the literature, ownership theory suggests that political parties receive support based on the issues for which they have a power of competence (Budge and Farelie 1983; Petrocik 1996). This type of support only occurs when the issues are salient (Bélanger and Meguid 2008). For instance, in the US, the Democratic Party is known as the party to manage "education, welfare, and civil rights", whereas the Republican Party has been known as the party to deal with "foreign affairs, national defense, and crime" (Petrocik 1996: p.837). In the context of issue ownership theory, people allocate issue ownership to the parties based on their understanding of the governance of these parties. In other words, parties who possess the issues already have experience as a ruling party. This phenomenon differs from economic voting theory, which indicates that people would support the parties without governing experience.

According to the literature, two topics become salient after natural disasters: economic growth and welfare (e.g., Oliver and Reeves 2015). Regarding economic growth, because disasters cause significant economic damage, how to return to normal life and how to recover from the damage are critical problems. As indicated by Visconti (2018), disaster victims make political decisions based on the expected benefits they will receive because welfare can help people recover from a disaster; thus, welfare is a focus of policy after disasters. Accordingly, based on issue ownership theory, the existing opposition parties that possess a reputation of competence concerning these two topics are more likely to be supported by people. To demonstrate whether economic voting theory or issue owner theory is more suitable to assess the impact of disasters on opposition party support, an empirical analysis is necessary.

CHAPTER 3
Behaviors toward Foreigners

3.1 Introduction

Using an original prefecture-level panel data in Japan, this chapter attempts to estimate the social impact of natural disasters on the behaviors of natives toward foreigners. According to the literature (e.g., Doidio et al. 2010), three types of attitudes and behaviors are taken by native people toward foreigners: prejudice, stereotyping, and discrimination. Because discrimination is a behavior that appears to harm to foreigners; therefore, it is the most important index to indicate the relationship between native people and foreigners. For this reason, this study uses the discrimination of native people toward foreigners as an indicator to measure behavior.

Furthermore, as disaster researchers have mentioned (e.g., Keerthiratne and Tol 2018; Matsubayashi, Sawada, and Ueda 2013; Yamamura 2015), the impact of disasters is not limited into the short-term, that is, long-term effects on society are also possible. Therefore, to explore the long-term effect of disasters on discrimination, this study also applies the time lag of a disaster's impact in the analyses. Additionally, as indicated by Matsubayashi, Sawada, and Ueda (2013), who used prefecture-level panel data, the general effect of disasters on societies may be strongly altered by extreme disasters. Extreme disasters, such as the Great East Japan Earthquake, damage societies more than smaller disasters; thus, the total effect of disasters on societies may only be attributed to extreme disasters. To identify this point, a comparative analysis must be conducted with and without extreme disasters.

The outline of this chapter is as follows. First, the methods that include the dataset, variable measurement, and analytical methods are presented. Then, the results are divided into three parts: 1) the results without time lag; 2) the results with time lag; and 3) the results with a time lag and without the year with extreme disasters. Finally, a short conclusion is provided.

3.2 Methods

3.2.1 Data

This chapter uses the original panel dataset collected from the 47 prefectures in Japan from 1999 to 2015. The total number of observations is 799 prefecture-years. The period of analyses was determined based on the availability of discrimination data. The discrimination data is collected by the Ministry of Justice (Hōmusho) in Japan, and the name of the set of statistics is Human Rights Violations (Jinken Shinpan Tōkei). The cases of discrimination against foreigners are counted based on the incidents judged to concern discrimination behaviors against foreigners such as refusing to allow foreigners to participate in social organizations. The data of disaster impact is collected by the Fire Disaster Management Agency (Shōbōcho), and the name of the set of statistics is the White Paper on the Fire Service (Shōbōhakusho). Other sources of this dataset are shown in Table 3.1.

Table 3.1 Sources of the Dataset

Variables	Source
Discrimination toward foreigners	From the Human Right Violations (Jinken Shinpan Tōkei) published by the Japanese Ministry of Justice (Hōmusho) (http://www.moj.go.jp/housei/toukei/toukei_ichiran_jinken.html)
Disaster-affected household number	From the White Paper on the Fire Service (Shōbōhakusho) published by Disaster Management Agency (Shōbōcho) (https://www.fdma.go.jp/publication/#whitepaper)
Household number	From the National Survey on Household Change (Setai Dotai Chōsa) published by the National Institution of Population and Social Security Research (http://www.ipss.go.jp/site-ad/index_Japanese/cyousa.html)
Total population	From the Japan Statistical Yearbook (Nihon Tōkei Nenkan) published by Statistics Bureau of Japan (https://www.stat.go.jp/data/index.html)
Area	From the Research of Prefecture Area (Zenkoku Todōfuken Shikuchōsonbetsu Mensekichō) published by Geospatial Information Authority of Japan (https://www.gsi.go.jp/KOKUJYOHO/MENCHO-title.htm)
Population of foreigners	From the Japan Statistical Yearbook (Nihon Tōkei Nenkan) published by Statistics Bureau of Japan (https://www.stat.go.jp/data/index.html)
gross domestic product (GDP)	From the Statistics on Economy of Citizens (Kenmin Keizai Seisan) published by Cabinet Office of Japan (https://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/main_h27.html)
Disaster recovery expenditure	From the White Paper on Local Public Finance (Chihō Zaisei Hakusho) published by the Ministry of Internal Affairs and Communications (http://www.soumu.go.jp/menu_seisaku/hakusyo/index.html)
NPO number	From the Statistics of NPO (NPO Tōkei Jyōhō) published by Cabinet Office, Government of Japan, NPO page (https://www.npo-homepage.go.jp/about/toukei-info)

3.2.2 Measurements

Dependent Variable

As mentioned in section 3.1, the discrimination of native people, namely, the Japanese against foreigners, is applied as the behavior toward foreigners. It is calculated by the division between the discrimination cases and the foreigner population norming the discrimination cases against the broader population in the prefecture. The equation is as follows.

$$FD_{it} = \frac{Foreigner\ Discrimination\ Cases_{it}}{Foreigner\ Population_{it}} \quad (3.1)$$

Where FD_{it} represents foreigner discrimination, and it is calculated as the ratio between the number of accepted and disposed foreigner discrimination and the foreigner population.

Independent Variable

This paper references the literature (Matsubayashi, Sawada, and Ueda 2013) and uses the proportion of households affected by natural disasters in prefectures each year as the disaster impact variable. It is calculated based on equation (3.2):

$$Disaster\ Impact_{it} = \frac{Disaster\ affected\ Household\ Number_{it}}{Household\ Number_{it}} \quad (3.2)$$

Controlling Variables

To control the characteristics that may affect both the dependent and independent variables, this study also includes controlling variables, based on the literature. The controlling variables are population density, women, elderly individuals (aged over 65 years), foreigner, disability (sum of population of physically handicapped persons, mentally handicapped persons, and cerebrally handicapped persons) proportion, employment rate, gross domestic product (GDP) per person, disaster recovery expenditure rate, and Nonprofit Organization (NPO) per person. The descriptive statistics of the variables are shown in Table 3.2.

Table 3.2 Descriptive Statistics of Variables

Variables	N	Mean	Standard Deviation	Min	Max
Dependent Variable					
Discrimination toward foreigners	799	0.661	1.037	0.000	8.313
Independent Variables					
Disaster impact	799	0.001	0.007	0.000	0.180
Disaster impact (t-1)	799	0.001	0.007	0.000	0.180
Disaster impact (t-2)	799	0.001	0.007	0.000	0.180

Disaster impact (t-3)	799	0.001	0.007	0.000	0.180
Controlling variables					
Population density (log)	799	1.197	0.982	-0.376	4.122
Women proportion	799	0.517	0.010	0.492	0.534
Elderly proportion	799	0.230	0.039	0.121	0.336
Foreigner proportion	799	0.012	0.007	0.002	0.034
Disability proportion	799	0.047	0.011	0.019	0.075
Employment rate	799	1.629	1.712	0.396	8.141
GDP per capita	799	3.696	0.772	2.523	8.325
Disaster recovery expenditure rate	799	0.008	0.014	0.000	0.190
NPO per person	799	0.000	0.000	0.000	0.001

3.2.3 Analytic Methods

To explore the relationship between natural disasters and discrimination against vulnerable groups, this study references by Matsubayashi, Sawada, and Ueda (2013) and uses the pooled regression model and fixed-effect model as the methods for analyses to check the robustness of results. To increase the clarity of this method, the equations and the meanings are as follows.

The pooled regression model can be generally expressed as follows:

$$D_{it} = \beta_0 + \beta_1 DI_{it} + \boldsymbol{\beta_{CV}} \boldsymbol{CV_{it}} + \beta_2 T_i + \beta_3 P_t + \varepsilon_{it} \quad (3.3)$$

Where D_{it} represents the discrimination against foreigners; DI_{it} equals the disaster impact, and $\boldsymbol{CV_{it}}$ is the vector of the control variables; β_1 and $\boldsymbol{\beta_{CV}}$ represent the regression coefficients of DI_{it} and $\boldsymbol{CV_{it}}$. T_i is year-specific fixed effects, and P_t indicates prefecture-specific fixed effects. ε_{it} expresses the error term, including time t and prefecture i.

Additionally, as mentioned in section 3.1, the literature concerning disasters has suggested that disasters may have a long-term effect on discrimination (Keerthiratne and Tol 2018; Matsubayashi, Sawada, and Ueda 2013; Yamamura 2015), and this study also applies a three time-lagged variable of disaster impact to the analyses. The equation can be expressed as follows:

$$D_{it} = \beta_0 + \beta_1 DI_{it} + \beta_2 DI_{it-1} + \beta_3 DI_{it-2} + \beta_4 DI_{it-3} + \boldsymbol{\beta_{CV}} \boldsymbol{CV_{it}} + \beta_5 T_i + \beta_6 P_t + \varepsilon_{it}$$
(3.4)

For the fixed-effect model, the equations can be expressed as follows:

$$\Delta D_{it} = \beta_1 \Delta DI_{it} + \boldsymbol{\beta_{CV}} \Delta \boldsymbol{CV_{it}} + \beta_2 \Delta T_i + \Delta\varepsilon_{it} \quad (3.5)$$

$$\Delta D_{it} = \beta_1 \Delta DI_{it} + \beta_2 \Delta DI_{it-1} + \beta_3 \Delta DI_{it-2} + \beta_4 \Delta DI_{it-3} + \boldsymbol{\beta_{CV}} \Delta \boldsymbol{CV_{it}} + \beta_5 \Delta T_i + \Delta\varepsilon_{it} \quad (3.6)$$

The models are basically the same as the pooled regression. Because the fixed-effect model attempts to eliminate the time-invariant effect of the regression model, each of the variables included in the equations is subtracted by their year-average with the mark of Δ. Additionally, because the prefecture-specific fixed effects have already been controlled by the subtraction, they will not be involved in the model again.

3.3 Results

3.3.1 Preliminary Analyses

Before the estimation of the pooled regression and fixed-effect model, to check the time trend of the main dependent and independent variables, the time trend of averaged dependent and independent variables is shown in Figure 3.1.

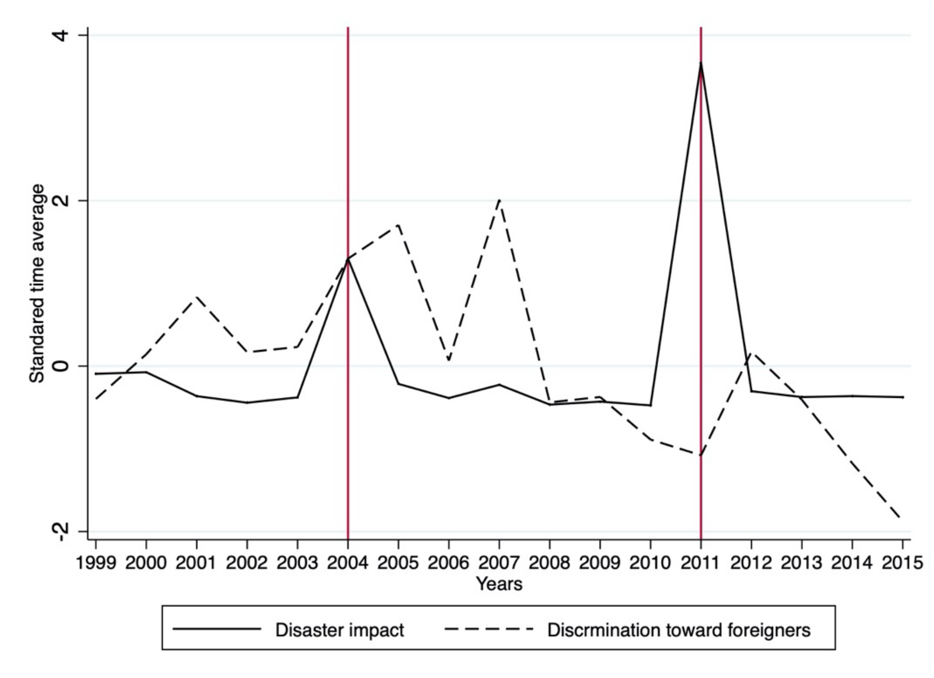

Figure 3.1 Time Trend of the Disaster and Discrimination against Foreigners

The standardized time-averaged variables of disaster impact and discrimination toward foreigners are included in Figure 3.1. The solid line is the time trend of disaster impact. There are two huge increases in disaster impact in 2004 and 2011, marked by the vertical lines. These two increases are caused by two huge earthquakes: the 2004

Chūetsu Earthquakes and the 2011 Great East Japan earthquake. Figure 3.1 also shows no potential relationship in the time trend between disaster impact and the discrimination against foreigners because the trend of the lines is different and irregular. However, this study includes the time variable to statistically control the potential relationship of the time trend for the statistic check.

3.3.2 Effects of Disasters on Discrimination

In this section, the relationship between disaster impact and discrimination is estimated through both the pooled regression and the fixed-effect model. At first, the disaster impact only at time t is included in the estimation, and the results are shown in Table 3.3.

Table 3.3 Results of the relationship between Disaster Impact and Discrimination against Foreigners

VARIABLES	Model 1	Model 2
Disaster impact	−19.75***	−19.75***
	(7.206)	(6.738)
Population density (log)	4.694**	4.694**
	(1.988)	(2.019)
Foreigner proportion	−35.11	−35.11
	(23.78)	(32.45)
Employment rate	−0.0384	−0.0384
	(0.0892)	(0.0855)
GDP per capita	0.267	0.267
	(0.287)	(0.279)
Disaster recovery expenditure rate	9.170***	9.170***
	(2.654)	(2.453)
NPO per person	−463.6	−463.6
	(553.5)	(693.4)
Constant	1.920	−5.694*
	(1.248)	(2.851)
Observations	799	799
R^2	0.208	0.063
Number of prefectures		47
Within R^2		0.0634
Between R^2		0.138

Overall R^2		0.0179
Year fixed effect	Yes	Yes
Prefecture fixed effect	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Two models are included in Table 3.3. Model 1 shows the results of pooled regression, and Model 2 shows the results of the fixed-effect model. In both models, after controlling all other variables, disaster impact has a negative and significant effect on the discrimination against foreigners, and the regression coefficients of disaster impact in these two models are also similar. These results mean that when one unit of disaster impact increases, approximately 19.75 units of discrimination will decrease.

Second, to explore the long-term effect of the disaster, the disaster impact at t - 1, 2, and 3 is included in the analyses. The results are shown in Table 3.4.

Table 3.4 Results of the relationship between Disaster Impact and Discrimination against Foreigners (with Time Lag)

VARIABLES	Model 3	Model 4
Disaster impact	−19.84***	−19.84***
	(7.239)	(6.928)
Disaster impact (t – 1)	−5.042	−5.042
	(4.692)	(4.437)
Disaster impact (t – 2)	4.438	4.438
	(5.911)	(5.302)
Disaster impact (t – 3)	0.228	0.228
	(4.526)	(3.967)
Population density (log)	4.675**	4.675**
	(1.993)	(2.018)
Foreigner proportion	−35.18	−35.18
	(23.96)	(32.35)
Employment rate	−0.0391	−0.0391
	(0.0890)	(0.0852)
GDP per capita	0.265	0.265
	(0.290)	(0.281)
Disaster recovery expenditure rate	9.130***	9.130***
	(2.950)	(2.781)

NPO per person	−468.7	−468.7
	(566.6)	(695.4)
Constant	1.929	−5.654*
	(1.250)	(2.860)
Observations	799	799
R^2	0.210	0.066
Number of prefectures		47
Within R^2		0.0657
Between R^2		0.138
Overall R^2		0.0177
Year fixed effect	Yes	Yes
Prefecture fixed effect	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Similar to Table 3.3, Table 3.4 has two models, and the results of the pooled regression and fixed-effect model are shown in Models 3 and 4, separately. Based on these results, in these two models, the disaster impact at t−1, 2, and 3 does not have significant effects on discrimination, whereas the disaster impact at t still has a negative and significant effect on discrimination. These results demonstrate that disasters have only a short-term, rather than a long-term, effect on discrimination.

Finally, to explore whether this impact on discrimination is altered by extreme disasters, an additional analysis is conducted that excludes the years 2004 and 2011, when 2004 Chūetsu Earthquakes and 2011 Great East Japan Earthquake occurred. The results are shown in Table 3.5.

Table 3.5 Results of the relationship between Disaster Impact and Discrimination against Foreigners (without 2004 and 2011)

VARIABLES	Model 5	Model 6
Disaster impact	74.67	74.67
	(70.79)	(74.41)
Disaster impact (t − 1)	−4.690	−4.690
	(4.618)	(4.539)
Disaster impact (t − 2)	4.806	4.806
	(5.972)	(4.803)

Disaster impact (t − 3)	0.359	0.359
	(4.288)	(3.706)
Population density (log)	5.037**	5.037**
	(2.124)	(2.430)
Foreigner proportion	−42.71*	−42.71
	(25.15)	(32.40)
Employment rate	−0.0401	−0.0401
	(0.0898)	(0.0742)
GDP per capita	0.317	0.317
	(0.297)	(0.247)
Disaster recovery expenditure rate	8.583***	8.583***
	(2.829)	(2.626)
NPO per person	−458.7	−458.7
	(576.2)	(634.1)
Constant	1.755	−6.203**
	(1.319)	(3.068)
Observations	705	705
R^2	0.228	0.068
Number of prefectures		47
Within R^2		0.0683
Between R^2		0.118
Overall R^2		0.0169
Year fixed effect	Yes	Yes
Prefecture fixed effect	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Table 3.5, two models are included, and they are Models 5 and 6, separately. The results show that after excluding the years 2004 and 2011, the effect of disaster impact becomes nonsignificant; thus, this effect is altered by extreme disasters. This finding implies that only huge disasters will have a decreasing effect on discrimination, whereas when small disasters occur, no changes will be observed in discrimination.

3.4 Conclusion

The major objective of the research in this chapter is to investigate whether and how disasters influence the behavior toward foreigners. Studies have argued that disasters may increase (Andrighetto et al. 2015) or decrease the negative attitudes and behaviors toward people from outgroups (Dovidio et al. 2004; Vezzali et al. 2015) on the basis of group threat theory (Stephan and Stephan 2000; Stephan et al. 2009) and the common ingroup identity model (Gaertner and Dovidio 2000, 2012); however, none have generally demonstrated the influence. This study used original panel data collected from the prefectures in Japan from 1999 to 2015 to empirically demonstrate the influence of disasters on the discrimination of native people against foreigners.

The results of both the pooled regression and fixed-effect model showed that natural disasters have a short-term effect of decreasing discrimination, and this effect was only observed in extreme disasters. The reason for these two appearances is discussed in Chapter 6. The results in this chapter provide empirical supportive evidence for the common ingroup identity model after disasters.

CHAPTER 4
Income Inequality

4.1 Introduction

As aforementioned, this study attempts to explore whether disasters decrease or increase income inequality from an individual perspective. The survey data collected to study society after the Great Eastern Japan Earthquake and tsunami is used as the dataset at the individual level. Because the questions in this data include employment status during and after the disaster, and unemployment affected by the disaster, an investigation into how the disaster affects income inequality through individuals' employment status is possible.

For the analyses, because this study attempts to completely reveal how disasters affect income inequality through the influence on individuals' employment and provide an empirical demonstration of the mechanism of this effect, four steps are progressively conducted in the analysis. The first step is to confirm social vulnerability theory in the short term. Studies have mentioned that people with lower socioeconomic status are more vulnerable, that is, more likely to lose their jobs in disasters. To confirm whether this theory is appropriate, analyses for the relationship between the employment status before a disaster and unemployment affected by a disaster will be conducted. If the results show that non-regularly employed workers have a higher probability to lose their job in a disaster, social vulnerability theory is valid.

The second step is to explore who is less likely to return to the same employment status after losing their job in a disaster. As mentioned in Chapter 2, according to the employment convention of the labor market, that is, employers prefer to hire non-regular employees to decrease costs, workers who were non-regularly employed are more likely to return to non-regular employment, and workers who were regularly employed are less likely to return to regular employment. An analysis of current employment status is conducted, and the interaction between unemployment affected by a disaster and employment status before a disaster is included. If the results show that compared with regularly employed workers, non-regularly employed workers are more likely to return to the same employment status, the market convention hypothesis is demonstrated.

The third step compares the income between disaster-affected non-regularly and regularly employed workers. Because non-regularly employed workers are more likely to return to the same employment status, compared with workers who were also non-regularly employed and not affected by the disaster, a notable difference in income is not observed. Because regularly employed workers are less likely to return to the same employment status, compared with workers who were also regularly employed and not affected by the disaster, income has a relatively huge difference.

The final step explores the mediating effect of current employment status. Because the different impact of disasters on individual income between regularly and non-regularly employed workers is caused by the difference in current employment status, the interaction effect between unemployment affected by the disaster and employment status before the disaster will be mediated by the current employment status. The analyses for individual income are conducted, and the interaction term between unemployment affected by disaster and employment status before the disaster, and current employment status, will be included. Figure 4.1 presents the aforementioned steps.

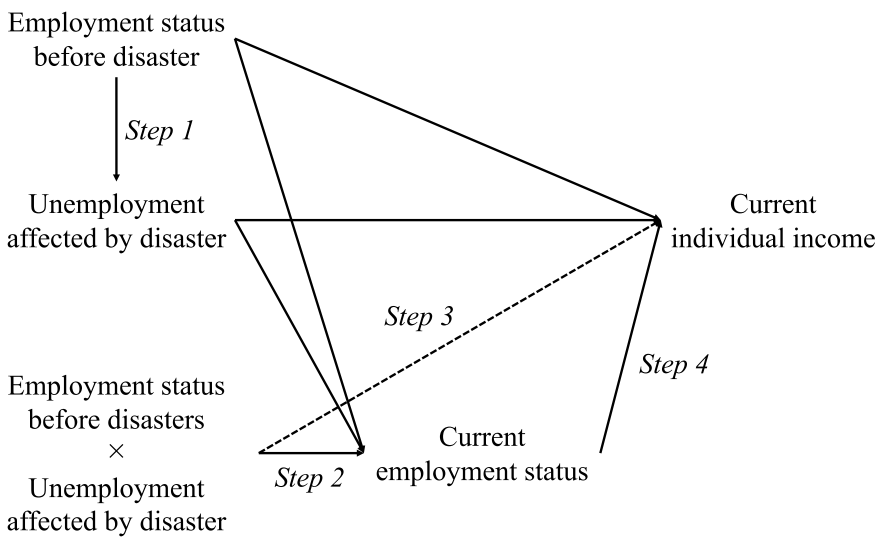

Figure 4.1 Analytic Structure of Chapter 4

The outline of this chapter is as follows. The chapter begins with a brief introduction to the dataset used for the analyses. Next, it empirically estimates the influence of disaster on income inequality by following the aforementioned three steps. To test the mediating effect of current employment status in the final step, the Wald test is to compare the regression coefficients of the interaction term in the two models. Finally, a short conclusion is provided as the last part of this chapter.

4.2 Methods

4.2.1 Data

Survey dataset called the *Questionnaire Survey on Work and Hopes following the Earthquake* is used in this study. The survey was conducted by Yuji Genda, a professor at the University of Tokyo, and implemented by an internet survey company in Japan. This survey aims to understand the changes in people's work and lifestyle three years after (2014) the Great Eastern Japan Earthquake and Tsunami. The survey range of this data is the Tohoku and Kanto regions in Japan, which were largely affected and damaged by the earthquake and tsunami. The population was the residents aged from 20 to 59 years (except students) of the Tohoku and Kanto regions. The number of respondents was 13,793, and the number of valid answers was 10,466 (collecting rate: 75.9%).

As mentioned in Chapter 4, because the mechanism of the influence of disasters on income inequality at the individual level focuses on the change in individuals' employment status. If people were unemployed before the disaster, they would not be affected by the disaster from the perspective of employment status. Additionally, because they were unemployed, they correspondingly did not have an individual income. This case is based on our aforementioned mechanism; thus, people who were unemployed before the disaster were excluded from our dataset.

4.2.2 Measurements

Dependent Variables

The main dependent variable is current individual income. This variable is measured by the question "Please tell me your individual income in the last year (2013)". The answer was from "No Income" to "JPY 15 million" in 13 categories. The median of each category is used as the income of that response.

Independent Variables

The analyses mainly use two independent variables: employment status in 2011 and unemployed in disaster. The employment status in 2011 is measured by the question "What is your current job?". The categories of this variable are "Company executive or manager," "Regular employee," "Part-time," "*Arubaito* (also part-time)," "Temporary," "*Hijyōkin* (also part-time)," "Daily-employed," "Dispatched employee," "Contract," "Contract employment," "*Shokutaku* (also part-time)," "Freeter (also part-time)," "Free-lance," "Independent contract," "Self-employment," "Family worker," "Side job," "Others." Finally, these categories are summarized as "Regular Employment," "Non-regular Employment," and "Self-employment."

The variable of unemployment affected by disaster is measured by the question "How was your work affected by the disaster: resignation." The categories were 1 "Yes" and 0 "No."

Mediating Variable

The mediating variable is the current employment status. It was asked in the same manner as the variable of employment status in 2011, and the categories are also the same. Therefore, also the summarized categories— "Regular Employment," "Non-regular Employment," "Self-employment," and "Unemployment"—are used in the analyses.

Controlling Variables

Considering that several confounder variables may simultaneously affect the independent and dependent variables, these variables are also included in the analyses, to control the confounding effect. These variables are sex, age, education, industry of job, general disaster impact, and residence in 2011. The descriptive statistics of the variables are summarized in Table 4.1.

Table 4.1 Descriptive Statistics of Variables

Variables	N	Mean/Percentage	Standard Deviation	Min	Max
Dependent variable					
Current individual income	3599	465.518	329.584	0.000	1750.000
Independent variables					
Employment status before disaster	3599				
Regular employment	2541	70.600			
Non-regular employment	888	24.670			
Self-employment	170	4.720			
Unemployment affected by disaster	3599				
Nonaffected	3441	95.610			
Affected	158	4.390			
Mediating variable					
Current employment status	3599				
Regular employment	2427	67.440			
Non-regular employment	746	20.730			
Self-employment	173	4.810			
Unemployment	253	7.030			
Controlling variables					

Sex	3559				
Male	2166	60.860			
Female	1393	39.140			
Age	3599	40.775	9.318	20.000	59.000
Education	3599	3.986	1.380	1.000	6.000
Industry of job in 2011	3599				
Primary	24	0.670			
Secondary	976	27.120			
Tertiary	2599	72.210			
Perceived disaster impact	3599	1.312	0.506	1.000	3.000
Residence in 2011	3599				
Kanto	2961	82.270			
Tohoku	638	17.730			

4.2.3 Analytic Methods

Because there are three steps in the analysis, the methods are introduced in three parts. The first part concerns the relationship between employment status before a disaster and unemployment in a disaster. Because unemployment in a disaster is a binomial variable, the method of logistic regression should be applied for analyses, and the equation is as follows:

$$ln\left[\frac{\Pr\,(Y_i=UD)}{1-\Pr\,(Y_i=UD)}\right] = \beta_0 + \beta_1 ES2011_i + \boldsymbol{\beta_{CV}}\boldsymbol{CV_i} \quad (4.1)$$

In equation 4.1, $ln\left[\frac{\Pr\,(Y_i=UD)}{1-\Pr\,(Y_i=UD)}\right]$ represents the logarithm of the odds ratio between unemployment being affected by a disaster or not. β_0 expresses the constant of the model; $ES2011_i$ and $\boldsymbol{CV_i}$ represent the employment status before a disaster and the vector of the controlling variables, respectively; β_1 and $\boldsymbol{\beta_{CV}}$ are their coefficients.

The second part is the interaction effect between unemployment in a disaster and employment status to current employment status. Because the employment status change is also a multinomial variable, the method of multinomial logistic regression is applied to the analyses, and the equation is as follows:

$$ln\left[\frac{\Pr(Y_i=Non-regular)}{\Pr(Y_i=Regular)}\right] = \beta_{10} + \beta_{11}ES2011_i + \beta_{12}UD_i + \beta_{13}ES2011_i * UD_i + \boldsymbol{\beta_{1CV}CV_i}$$
$$ln\left[\frac{\Pr(Y_i=Self-employment)}{\Pr(Y_i=Regular)}\right] = \beta_{20} + \beta_{21}ES2011_i + \beta_{22}UD_i + \beta_{23}ES2011_i * UD_i + \boldsymbol{\beta_{2CV}CV_i}$$
$$ln\left[\frac{\Pr(Y_i=Unemployment)}{\Pr(Y_i=Regular)}\right] = \beta_{30} + \beta_{31}ES2011_i + \beta_{32}UD_i + \beta_{33}ES2011_i * UD_i + \boldsymbol{\beta_{3CV}CV_i} \quad (4.2)$$

In this equation, the regular employment of current employment status is set as the reference category for the dependent variable, and it is represented as $\Pr(Y_i = Regular)$ in equation (4.2). Additionally, $\Pr(Y_i = Non-regular)$ represents the probability of non-regular employment; $\Pr(Y_i = Self-employment)$ is the probability of self-employment; and $\Pr(Y_i = Unemployment)$ expresses the probability of unemployment. $ES2011_i * UD_i$ represents the interaction term between unemployment affected by a disaster and employment status before a disaster, and β_{13}, β_{23}, and β_{33} are its regression coefficients.

The third- and fourth-part focus on the interaction effect between unemployment in a disaster and employment status before a disaster on current individual income, and the mediating effect of current employment status. Because individual income is a continuous variable, the OLS regression is conducted in the analysis, and the equation is as follows:

$$CII_i = \beta_0 + \beta_1 ES2011_i + \beta_2 UD_i + \beta_3 ES2011_i * UD_i + \boldsymbol{\beta_{CV}CV_i} + \varepsilon_i \quad (4.3)$$
$$CII_i = \beta_0 + \beta_1 ES2011_i + \beta_2 UD_i + \beta_3 ES2011_i * UD_i + \beta_4 CES_i + \boldsymbol{\beta_{CV}CV_i} + \varepsilon_i \quad (4.4)$$

In equations 4.3 and 4.4, CII_i represents current individual income. In equation 4.4, the CES_i, which represents the current employment status, is added into the model, and β_4 is its regression coefficient. By comparing the β_3 in equation 4.3 and β_3 in equation 4.4, whether the interaction effect is mediated by the current employment status can be understood.

4.3 Results

Again, because the analyses are divided into three parts, the results are shown in three parts. The first part shows the result of the relationship between employment status before a disaster and unemployment in a disaster, and its summary is in Table 4.2.

Table 4.2 Results of Unemployment Affected by the Disaster

VARIABLES	Model 1
Employment status before a disaster (Ref: regular employment)	
Non-regular employment	1.158***
	(0.274)
Self-employment	−0.273
	(0.738)
Sex (Ref: female)	0.013
	(0.275)
Age	−0.015
	(0.013)
Education	−0.018
	(0.088)
Industry (Ref: tertiary industry)	
Primary industry	n.s.
Secondary industry	−0.010
	(0.291)
Disaster impact	0.884***
	(0.192)
Residence in 2011 (Ref: Kanto)	0.620*
	(0.260)
Constant	−5.030***
	(0.729)
Observations	3599
G^2	59.916***
Nagelkerke R^2	0.089

Standard errors are in parenthesis

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4.2 has one model and shows that for employment status before a disaster, only non-regular employment has a positive and significant effect on unemployment in a disaster, and self-employment does not. This result means that compared with workers who were regularly employed, non-regularly employed workers are more likely to lose their job in a disaster.

Figure 4.2 is presented to increase the clarity of the following: the difference of being unemployment affected by disaster between regular and non-regular employment. The circle represents the mean of the predicted probability of unemployment being affected by a disaster in each type of employment status. Figure 4.2 also demonstrates that non-regularly employed workers before a disaster are more likely to lose their job than both regularly and self-employed workers because their probability is much higher than the workers with these two types of employment status.

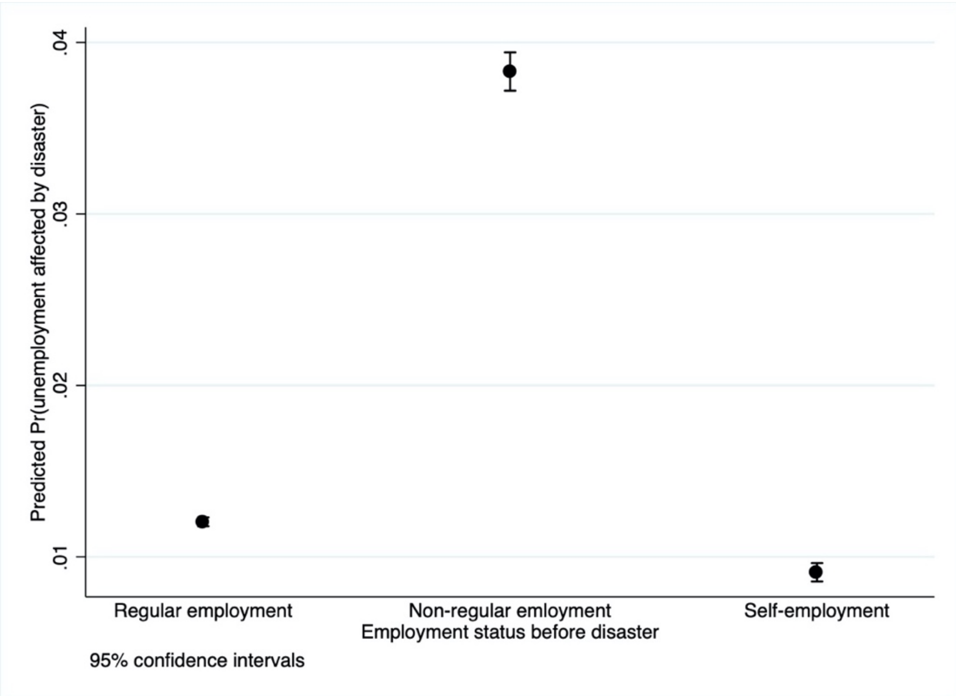

Figure 4.2 Average Probability of Unemployment Being Affected by Disaster in Each Employment Status

The second part shows the interaction effect between employment status before a disaster and unemployment in a disaster on current employment status. The results are summarized in Table 4.3.

Table 4.3 Results of Current Employment Status

	Model 2			Model 3		
VARIABLES	Non-regular	Self-employment	Unemployment	Non-regular	Self-employment	Unemployment
Unemployment affected by disaster (Ref: nonaffected)	2.045***	2.526***	2.450***	2.770***	2.103	2.580***
	(0.421)	(0.658)	(0.439)	(0.442)	(1.078)	(0.563)
Employment status before disaster (Ref: regular employment)						
Non-regular employment	4.864***	3.965***	3.672***	4.950***	3.931***	3.713***
	(0.166)	(0.373)	(0.196)	(0.171)	(0.384)	(0.200)
Self-employment	2.984***	7.679***	3.042***	3.026***	7.627***	3.048***
	(0.440)	(0.436)	(0.483)	(0.441)	(0.437)	(0.484)
Unemployment affected by disaster* Employment status before disaster						
Affected by disaster*Non-regular employment				−2.952***	−1.291	−2.175*
				(0.785)	(1.435)	(0.893)
Affected by disaster*Self-employment				−3.847	19.36	−4.354
				(246,255)	(120,798)	(347,784)
Sex (Ref: female)	−1.659***	0.205	−2.172***	−1.684***	0.206	−2.184***
	(0.158)	(0.307)	(0.204)	(0.159)	(0.307)	(0.205)
Age	0.0217**	0.00236	−0.0153	0.0218**	0.00271	−0.0153
	(0.00802)	(0.0156)	(0.00941)	(0.00805)	(0.0157)	(0.00942)
Education	−0.128*	0.0418	−0.239***	−0.128*	0.0398	−0.240***
	(0.0533)	(0.104)	(0.0622)	(0.0535)	(0.104)	(0.0623)
Industry (Ref: tertiary industry)						

Primary industry	1.198	3.270**	0.998	1.202	3.257**	0.991
	(1.023)	(1.036)	(1.211)	(1.031)	(1.030)	(1.212)
Secondary industry	−0.405*	−1.150**	−0.497*	−0.407*	−1.146**	−0.493*
	(0.180)	(0.399)	(0.218)	(0.180)	(0.399)	(0.218)
Disaster impact	−0.0617	0.478	−0.00346	−0.0577	0.485	0.000
	(0.142)	(0.251)	(0.163)	(0.142)	(0.252)	(0.163)
Residence in 2011 (Ref: Kanto)	−0.151	−0.307	−0.505*	−0.161	−0.322	−0.507*
	(0.191)	(0.355)	(0.229)	(0.191)	(0.356)	(0.229)
Constant	−2.328***	−6.058***	−0.635	−2.365***	−6.024***	−0.631
	(0.439)	(0.880)	(0.494)	(0.441)	(0.881)	(0.495)
Observations	3,599	3,599	3,599	3,599	3,599	3,599
G^2		3477.464***			3488.338***	
Nagelkerke R^2		0.735			0.737	

Standard errors in parentheses

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4.3. presents two models. Model 2 shows the results without the interaction term. In Model 2, the coefficient of unemployment affected by disaster in each column is significantly positive; thus, compared with being regularly employed, disaster-affected people are more likely to change to other types of employment status. However, through Model 2, only the comparison between regular employment and others can be understood; thus, a comparison among other employment statuses has not been conducted. To provide a simple result of the influence of disaster on current employment status, the average marginal effect of unemployment affected by disaster on each current employment status is conducted in Table 4.4. The results show that the marginal effect on-regular employment is significantly negative, and it is significantly positive on non-regular employment and unemployment. These results imply that generally, people who are unemployed and affected by the disaster have a high probability to change to non-regular employment or remain unemployed rather than regular employment.

Table 4.4 Marginal Effect of Unemployment Affected by Disaster

Marginal effect on the probability of	Average marginal effect of unemployment affected by disaster
Regular employment	−0.495***
	(0.082)
Non-regular employment	0.255***
	(0.073)
Self-employment	0.053
	(0.037)
Unemployment	0.187***
	(0.058)

Delta-mentioned standard errors in parentheses

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

In Model 3, the interaction term is included in the analysis. In the column of non-regular employment, the interaction term shows that non-regular employment and disaster effect are significantly and negatively associated with non-regular employment, and the main effect of disaster effect is significantly and positively associated with it. Because the coefficient of the interaction term is −2.952, and it is 2.770 in the main effect of disaster effect, the disaster effect in non-regular employment is −0.182. These results suggest that workers who were regularly employed before a disaster are more likely to obtain non-regular employment, and workers who were non-regularly employed are less likely to be affected by a disaster. Additionally, in the column of unemployment, the interaction term also shows that non-regular employment and disaster effect are significantly and negatively associated with being unemployment, and the main effect of disaster effect is significantly and positively associated with it. The coefficient of the main effect of disaster effect is 2.580, and it is −2.175 in the interaction term; thus, the effect of disaster on non-regular employment is 0.405. These results suggest that the workers who were regularly and non-regularly employed have a probability of becoming unemployed; however, regularly employed workers are more likely to become unemployed compared with non-regularly employed workers affected by the disaster. Summarily, workers who were regularly employed are more likely to become non-regularly employed and unemployed, and workers who were non-regularly employed are more likely become to regularly employed and less likely to become unemployed. According to these two points, an observation could be that non-regularly employed workers would have the same or higher employment status and regularly employed workers would have a lower employment status after a disaster.

To provide a more direct result to understand which employment status is more likely to return to the same or higher employment status, an additional analysis using the change in employment status as the dependent variable is conducted. The people whose current employment status is same or higher than before are included as 1. The people whose current employment status is lower (including unemployment) than before are included as 0. The results are shown in Table 4.5.

Table 4.5 Change in Employment Status

VARIABLES	Model 4	Model 5
Unemployment affected by disaster (Ref: nonaffected)	−1.372***	−2.255***
	(0.274)	(0.350)
Employment status in 2011 (Ref: regular employment)		
Non-regular employment	−0.072	−0.165
	(0.131)	(0.133)
Self-employment	−0.452	−0.544*
	(0.257)	(0.258)
Unemployment affected by disaster*Employment status in 2011		
Affected*Non-regular employment		1.699***
		(0.506)
Affected*Self-employment		n.s.

Sex (Ref: female)	1.587***	1.632***
	(0.144)	(0.147)
Age	0.026***	0.026***
	(0.006)	(0.006)
Education	0.191***	0.186***
	(0.044)	(0.044)
Industry (Ref: tertiary industry)		
Primary industry	−0.122	−0.109
	(0.662)	(0.663)
Secondary industry	0.437**	0.454**
	(0.157)	(0.158)
Disaster impact	−0.065	−0.063
	(0.113)	(0.112)
Residence in 2011 (Ref: Kanto)	0.277	0.281
	(0.155)	(0.155)
Constant	−0.257	−0.212
	(0.346)	(0.347)
Observations	3599	3599
G^2	337.261***	354.157***
Nagelkerke R^2	0.181	0.190

Standard errors are in parenthesis

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4.5. has two models. Model 4 shows the results without the interaction term, and unemployment affected by disaster is negatively and significantly associated with employment status change. This result means that generally, compared with people not affected by the disaster, people affected by the disaster are less likely to return to their original employment status.

The result of the interaction term in Model 5 shows that non-regular employment and disaster effect are positively and significantly associated with employment status change, and the main effect of disaster-affect is negatively and significantly associated with it. The coefficient of the main effect is −2.255, and it is 1.699 in the interaction term of on-regular employment and disaster-affect. The sum of these coefficients represents the effect of disaster on non-regular employment, and it is −0.556, much smaller than that on-regular employment, which is −2.255. These results mean that compared with workers who were regularly employed, non-regularly employed workers find it less difficult to return to the same or higher employment status. The coefficient of the interaction term between unemployment affected by disaster and self-employment before disaster is n. s., which means that no cases of self-employment are affected by the disaster in this dataset.

Figure 4.2 presents the results and confirms that the slope of regular employment before a disaster is shaper than non-regular employment; thus, non-regularly employed workers have a less difficult time when attempting to return to the same or higher employment status.

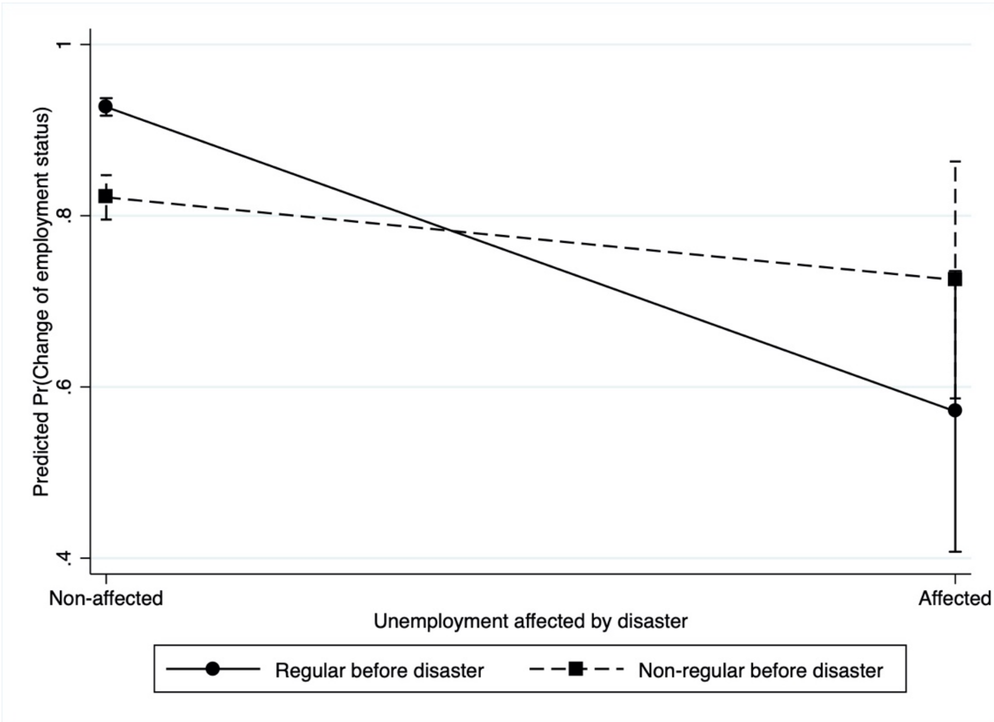

Figure 4.3 Interacting Effect of Disaster Effect and Employment Status on Change in Employment Status

Next, it shows the interaction effect between employment status before a disaster and unemployment in a disaster on current individual income, and the mediating effect of current employment status. The results are summarized in Table 4.6.

Table 4.6 Results of Current Individual Income

	Model	Model
VARIABLES	6	7
Unemployment affected by disaster (Ref: nonaffected)	−226.326***	−145.802***
	(39.852)	(38.846)
Employment status before disaster (Ref: regular employment)		
Non-regular employment	−254.392***	−93.305***
	(10.469)	(15.325)
Self-employment	−229.454***	−116.850***
	(19.205)	(29.999)
Unemployment affected by disaster* Employment status before disaster		
Affected*Non-regular employment	175.295***	100.089
	(54.810)	(53.235)
Affected*Self-employment	214.474	130.532
	(170.863)	(165.181)
Current employment status (Ref: regular employment)		
Non-regular employment		−203.220***
		(15.989)
Self-employment		−128.518***
		(29.937)
Unemployment		−280.420***
		(18.382)
Sex (Ref: female)	175.495***	139.556***
	(9.353)	(9.349)
Age	8.935***	8.946***
	(0.444)	(0.430)
Education	46.072***	43.189***
	(2.941)	(2.847)
Industry (Ref: tertiary industry)		
Primary industry	17.245	29.958
	(49.053)	(47.600)
Secondary industry	38.298***	32.707***
	(9.011)	(8.718)
Disaster impact	7.003	6.726
	(7.924)	(7.660)
Residence in 2011 (Ref: Kanto)	−65.960***	−71.633***

	(10.590)	(10.236)
Constant	−119.686***	−62.113**
	(24.458)	(23.923)
Observations	3599	3599
Adjusted R^2	0.499	0.533

Standard errors are in parenthesis

*** p < 0.001, ** p < 0.01, * p < 0.05

Table 4.6 has two models. Model 6 represents the interaction effect between unemployment affected by disaster and employment status before disaster in current individual income, and Model 7 contains the mediating variable of current employment status. In Model 6, the result of the interaction term shows that disaster-affected non-regular employment is positively and significantly associated with individual income, and the main effect of disaster-affect is negatively and significantly associated with it. The coefficient of the main effect is −226.326, and it is 175.295 in the interaction term of disaster-affected non-regular employment. The main effect represents the influence of disaster among workers who were regularly employed, and the sum of the main effect and the interaction term of non-regular employment and disaster-affect, which is −51.031 (=−226.326+175.295), represents the influence of a disaster among workers who were non-regularly employed. Because −51.031 is much smaller than −226.326, the results suggest that compared with workers who were regularly employed, non-regularly employed workers have a smaller difference in current individual income compared with nonaffecteds workers.

Figure 4.7 presents the results and confirms that the slope of regular employment before a disaster is shaper than non-regular employment, meaning that non-regularly employed workers have less difference in current individual income compared with nonaffected workers.

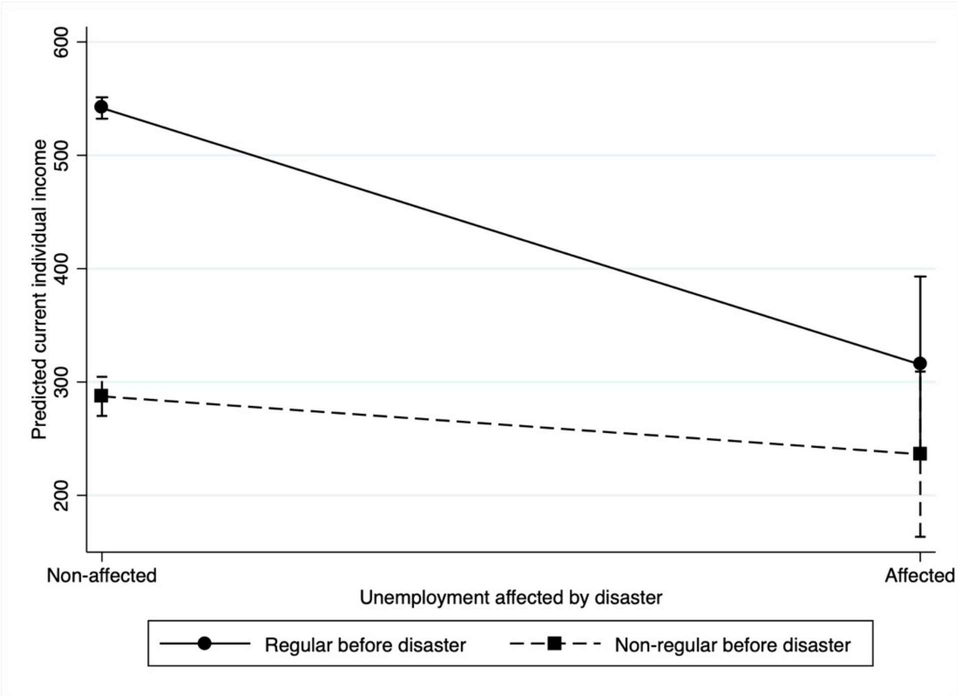

Figure 4.4 Interacting Effect of Disaster Effect and Employment Status on Current Individual Income

Model 5 shows the results after the inclusion of current employment status, and the coefficient of the interaction term in disaster-affected and non-regular employment becomes smaller and nonsignificant. According to the principle of mediation in regression models, the coefficients of the variables become smaller and nonsignificant when another variable is included, meaning that the effects of the variables are mediated by another variable. Therefore, the effect of the interaction term is mediated by the current employment status.

Furthermore, to check whether this change of coefficient is statistically significant, the additional seemly unrelated estimation and a Wald test are conducted, and the results are shown in Table 4.7. The p value in Table 4.5 is 0.0006, which is smaller than 0.001; thus, the difference in the coefficients in Models 4 and 5 is statistically significant. Accordingly, the interaction effect is mediated by current employment, meaning that the different impact of a disaster between regularly and non-regularly employed workers on current individual income is realized through the current employment status.

Table 4.7 Wald test of the Interaction Term

Variable	Seemly unrelated estimation		Wald test		
	Model 4	Model 5	Difference	Chi2	p value
Affected*Non-regular employment	175.295	100.089	75.206	11.75	0.0006

4.4 Conclusion

Studies concerning the impact of disasters on income inequality have provided results after using data at the macrolevel. However, because the analyses at the macrolevel could not provide evidence to empirically prove the mechanism mentioned in the studies, the individual approach is necessary. This study uses the data collected at the individual level after the Great Eastern Japan Earthquake and tsunami and completes four steps to demonstrate how and why disasters influence income inequality. The empirical analyses yielded three main findings: first, consistent with social vulnerability theory, in the short term, non-regularly employed workers were more likely to lose their job in the disaster compared with regularly employed workers; second, however, because of the employment convention of the labor market, non-regularly employed workers have a less difficult time when they endeavor to return to the same or higher employment status compared with regularly employed workers; finally, throughout this approach, non-regularly employed workers have a smaller difference in current individual income, and regularly employed workers have bigger difference compared with nonaffected workers. Through these results, in the short term, income inequality will increase because people with lower socioeconomic status are more likely to lose a job in a disaster. In the long term, although the results show that the income difference between regularly and non-regularly employed workers decreased affected by the disaster, in a broader view, because people with a lower socioeconomic status in the whole society increased, the macrolevels of inequality of individual income may also be promoted after the disaster. This conclusion provides empirical evidence at the individual level to support the literature conducted at the macrolevel, which suggested that disasters expand the income inequality.

CHAPTER 5
Opposition Party Support

5.1 Introduction

As mentioned in Chapter 2, according to economic voting theory and issue owner theory, impacts of natural disasters on opposition parties' support have two hypotheses: disasters increase the support for challenger parties, and disasters increase the support for parties with experience in government. This study uses data collected from the individual and prefectural level in Japan to provide empirical evidence that proves these two hypotheses.

The outline of this chapter is as follows. First, an introduction to the party system and the political situation in Japan is provided. Through the introduction, the party system and the characteristics of the parties in Japan can be understood. Next, a brief statement is made on the two datasets used in this study, and the variable measurements and analytical methods are introduced. Then, the results of the two datasets are shown separately in the results section. Finally, a short conclusion based on those results is provided.

5.2 Party System and Parties in Japan

Different from the two-party system of the US, Japan applies the multiparty system, as do most European countries. After World War II, Japan was occupied by the US, and the US wanted to apply a new party system in Japan. After the US occupation, in 1955, the *1955 System*, which describes a political situation where the Liberal Democratic Party (LDP), the ruling party, and the Japan Socialist Party (JSP), the biggest opposition party in Japan, was established. This system was sustained for approximately 38 years (Masumi 1988) and ensured the political power of the LDP; thus, the LDP became the most experienced party in governance in Japan. After 1960, the JSP started to disintegrate into other small parties and dissolved in 1996. Therefore, after 1996, the JSP had no power to manage disasters. The *1955 System* ended in 1993 and was marked by the replacement of the ruling party. In 1996, the LDP was again elected as the ruling party until 2009, and after 2012, the LDP again became the ruling party.

After the changes to and recombination of the opposition parties, in 2005, the political situation stabilized. At this time, the Democratic Party of Japan (DPJ) became the most powerful opposition party and was elected as the ruling party in 2009. Three other mainstream opposition parties operate within the Japanese political system: Kōmeitō, the Japanese Communist Party (JCP), and the Social Democratic Party (SDP).

Other new parties have also emerged, such as the People's New Party, Your Party, and the Japanese Innovation Party.

In the LDP period, the economy of Japan rapidly grew from 1960 until the bubble collapse; thus, the LDP has been responsible for economic growth. Compared with the LDP, the DPJ proposed more policies that concerned social welfare (Fujita and Matsui 2018); thus, the DPJ possesses the advantage of welfare. These two parties are consistent with the parties mentioned in issue ownership theory (Chapter 2); therefore, the LDP and DPJ are deemed the parties with issue ownership of economic growth and welfare, separately, after the disasters.

By contrast, according to Hobolt and Tilley (2016), the challenger parties are defined as the parties that are relatively new and have not been elected as the ruling party. Through this definition, the parties that emerged after 2005 in Japan, such as the People's New Party, Your Party, and the Japanese Innovation Party, can be deemed the challenger parties.

The other long-established opposition parties, such as Kōmeitō, the JCP, and the SDP, are treated as the traditional opposition parties. Accordingly, four categories of parties are involved in the analyses: LDP, DPJ, traditional opposition parties, and challenger parties.

5.3 Methods

5.3.1 Data

Two types of datasets are used in this study. The first dataset is at the individual level and is called the *Survey on the Image of Foreign Countries and Current Topics*. The data were collected after the Great Eastern Japan Earthquake and tsunami. The Research Institute of Contemporary Japanese Systems, Waseda University, conducted this survey, and it was implemented by an internet survey company in Japan. This survey aims to understand the attitudes of Japanese people toward politics, national defense, and foreign diplomacy after the disaster. The population of this survey is all Japanese people aged over 20 years. The survey generally has 24 waves, surveyed from 2011 to 2013 monthly; and part of the samples is the panel, and other parts are refreshed. Because only wave six asked the perceived disaster impact, this study could only apply the wave six datasets to the analyses. Additionally, because people who lived in the Tohoku and Kanto regions were affected more in the disaster than those in other regions, this study only uses the sample collected in the Tohoku and Kanto regions (N=1,326).

The second dataset is an original panel dataset collected from the 47 prefecture-level administrative regions of Japan from 2004 to 2015. The sources of the data are from statistical reports of the Government of Japan, such as from the Cabinet

Office of Japan, the Ministry of Internal Affairs and Communication of Japan, and the Japan Meteorological Agency. The sources of the data are shown in Table 5.1.

Table 5.1 Sources of Dataset

Variables	Source
DPJ, LDP, traditional opposition party, and challenger party voting share	From the Data concerning Vote (Senkyo Kanren Shiryō) published by the Ministry of Internal Affairs and Communication (Sōmushō) http://www.soumu.go.jp/senkyo/senkyo_s/data/index.html
Disaster-affected household number	From the White Paper on the Fire Service (Shōbōhakusho) published by Disaster Management Agency (Shōbōcho) (https://www.fdma.go.jp/publication/#whitepaper)
Household number	From the National Survey on Household Change (Setai Dotai Chōsa) published by the National Institution of Population and Social Security Research (http://www.ipss.go.jp/site-ad/index_Japanese/cyousa.html)
Total population	From the Japan Statistical Yearbook (Nihon Tōkei Nenkan) published by Statistics Bureau of Japan (https://www.stat.go.jp/data/index.html)
Area	From the Research of Prefecture Area (Zenkoku Todōfuken Shikuchōsonbetsu Mensekichō) published by Geospatial Information Authority of Japan (https://www.gsi.go.jp/KOKUJYOHO/MENCHO-title.htm)
Population of women and elderly people	From the Japan Statistical Yearbook (Nihon Tōkei Nenkan) published by Statistics Bureau of Japan (https://www.stat.go.jp/data/index.html)
GDP	From the Statistics on Economy of Citizens (Kenmin Keizai Seisan) published by Cabinet Office of Japan (https://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/main_h27.html)
Disaster recovery expenditure	From the White Paper on Local Public Finance (Chihō Zaisei Hakusho) published by the Ministry of Internal Affairs and Communications (http://www.soumu.go.jp/menu_seisaku/hakusyo/index.html)
Vote rate	From the Data concerning Vote (Senkyo Kanren Shiryō) published by the Ministry of Internal Affairs and Communication (Sōmushō) http://www.soumu.go.jp/senkyo/senkyo_s/data/index.html

These two datasets were used for the following two reasons. First, because the sample size of the model when the DPJ was ruling party is too small. From 2004 to 2015, except for the LDP, only the DPJ became the ruling party, and the period was from 2010 to 2012. In this period, only two elections were conducted; therefore, the sample size of the model when the DPJ was ruling party is too small (N=94) for analyses, and the results may be unreliable. Because the individual data were collected on March 16, 2012, when the DPJ was ruling party, it can be used to double-check the results conducted at the macrolevel. Second, through the results of these two datasets, the general trend of the opposition party support can be captured because these two datasets include both extreme examples (individual data) and the general situation (prefectural data).

5.3.2 Measurements

Because this study uses two datasets for analyses, and they at different levels, all the variables are measured differently at these two levels.

Dependent Variables

As mentioned in section 5.2, this study generally classifies the parties in Japan into four categories: LDP, DPJ, traditional opposition parties, and challenger parties; therefore, the dependent variables are the supports to the parties in these four categories. At the individual level, these supports are measured by the question "Which party do you support? (Only one answer)". The answers are "LDP," "DPJ," "Kōmeitō," "JCP ", "SDP," "YP," "Other Parties," and "Nonsupport." Here, "LDP" and "DPJ" are the supports to LDP and DPJ, separately; "Kōmeitō," "JCP," and "SDP" are summarized as the support for traditional opposition parties; "YP" and "Other Parties" are deemed as the support for challenger parties; and "Nonsupport" is no party support.

At the prefectural level, the voting share in the elections for these parties in each prefecture is used as the support for them. There are two types of election systems in Japan: proportional representation (*Hireidaihyō*) (PR) and a single-seat constituency (*Shōsenkyoku*) (SC) election system. PR refers to distributing the legislative seats on the basis of the obtained votes for each party. Because the distribution of the seats is determined by the obtained votes, even the small party has an opportunity to obtain the seats. Therefore, almost every party choose the candidates for the assembly members in every election. Additionally, because a small party can participate in the discussion and determination of national affairs, the voice and opinions from disaster-affected people, which can be treated as a small group, can also be conveyed to the leaders of the country.

By contrast, an SC election system refers to electing only one assembly member in one constituency. With this approach, only big parties benefit from this election because other small parties cannot win under this system. Therefore, the minor parties may not set the candidates in the constituencies if they think that they will not succeed in that constituency. Accordingly, this study uses party voting shares in the PR system because every party will set candidates, and the voice from the disaster-affected people can also be conveyed through this election.

Additionally, both the election of the House of Councilors (*Sangiin*) and House of Representatives (*Shūgiin*) are used in this study. Because the Councilors and Representatives elections are held in different years, exclusively, I treat their voting rate as the same thing and combine them in the same variable in different years. To control the differences between these two types of elections, I create a dummy variable for the analyses.

For the voting share of these parties, consistent with the classification of party support at the individual level, the voting shares of the LDP and DPJ are defined as the support for the LDP and DPJ, respectively; the voting shares of Kōmeitō, the JCP, and the SDP are summarized as the support for traditional opposition parties; and the voting shares of the parties such as the People's New Party, Your Party, and the Japanese Innovation Party are concluded as the support for challenger parties. The voting rates of these parties are calculated as the ratio between the number of voters and the population who have a right to vote.

Independent Variables

The independent variables are also divided into individual and prefectural levels. At the individual level, the disaster impact is measured by the perceived disaster impact by the following question, "On March 11, 2011, the Great Eastern Japan Earthquake caused severe damage to Japan, did you incur damage or have any experiences during this disaster?" The answers are "I did not incur damage or have a bad experience.", "I did not incur any damage, and the bad experience is also small .", "I did not incur any damage but experienced a big inconvenience such as blackout.", "I could stay at home although I incurred some damage.", and "I incurred damage and had to evacuate from my home.". The values are from 1 to 5.

At the prefectural level, the proportion of households affected by natural disasters in the prefectures each year is measured as the disaster impact variable. Because the calculation has already been shown in Chapter 3, it is omitted in this chapter. For the long-term effect of disasters on the voting share when the ruling party is the LDP, similar to Chapter 3, the disaster impacts at t−1, 2, and 3 are applied in the analyses.

Controlling Variables

At the individual level, the controlling variables are sex, age, education, marriage status, employment status, individual income, frequency of TV watching, frequency of newspaper reading, and frequency of internet usage. At the prefectural level, and by referencing a study conducted at the macrolevel (Healy and Malhatra 2010), this study uses population density, proportion of women, proportion of elderly people, employment rate, GDP per capita, disaster recovery expenditure rate, total vote rate, election type, and the proportion of challenger parties as the controlling variables. The descriptive statistics of the variables are summarized in Table 5.2.

Table 5.2 Descriptive Statistic of Variables

Variables	N	Mean/Percentage	Standard Deviation	Min	Max	Variables	N	Mean/Percentage	Standard Deviation	Min	Max
Individual level						**Prefectural level**					
Dependent variable						*Dependent variable*					
Opposition party support	1141					DPJ voting share	329	26.598	10.722	6.189	52.110
DPJ	177	15.510				LDP voting share	329	31.321	6.220	16.592	47.528
LDP	168	14.720				Traditional opposition party voting share	329	9.286	4.325	3.089	34.760
Traditional opposition party	60	5.260				Challenger party voting share	329	9.114	12.099	0.000	58.307
Challenger party	122	10.690				*Independent variable*					
Nonsupport	614	53.810				Disaster impact	329	2.530	9.604	0.000	121.778
Independent variable						Disaster impact (t - 1)	329	12.793	104.260	0.000	1814.229
Perceived disaster impact	1141	2.763	0.827	1.000	5.000	Disaster impact (t - 2)	329		102.064	0.000	1814.229
Controlling variables						Disaster impact (t - 3)	329		104.373	0.000	1814.229
Sex	1141					*Controlling variables*					
Male	628	55.040				Population density (log)	329	−5.717	0.992	−7.279	−2.794
Female	513	44.960				Proportion of women	329	0.518	0.010	0.494	0.533
Age	1141	46.688	13.752	20.000	70.000	Proportion of elderly people	329	0.248	0.032	0.161	0.327
Education	1141	3.417	0.822	1.000	4.000	Employment rate	329	0.478	0.046	0.343	0.671

Marriage	1141					GDP per capita	329	3603.714	795.278	2161.132	8325.374
Non-marriage	350	30.670				Disaster recovery expenditure rate	329	0.009	0.018	0.000	0.190
Married	791	69.330				Total vote rate	329	62.205	8.108	46.247	78.340
Employment status	1141					Election type	329				
Management or office	163	14.290				House of representative	141	42.860			
Regular employment	354	31.030				House of councilors	188	57.140			
Non-regular employment	164	14.370				Proportion of challenger party	329	0.254	0.248	0.000	0.583
Self-employment	114	9.990				Ruling party	329				
Unemployment	346	30.320				DPJ	141	25.000			
Individual income (log)	1141	6.362	0.665	4.610	7.314	LDP	423	75.000			
TV watching	1141	4.486	1.006	1.000	5.000						
Newspaper reading	1141	3.720	1.651	1.000	5.000						
Internet usage	1141	3.972	1.584	1.000	5.000						

5.3.3 Analytic Methods

Because the datasets are used at both the individual and prefectural level, the analyses are conducted at these two levels, separately. At the individual level, to compare the effect if perceived disaster impact on the support for the parties, multinomial logistic regression is applied for the analyses. The model can be expressed as follows:

$$ln\left[\frac{\Pr(Y_i=LDP)}{\Pr(Y_i=DPJ)}\right] = \beta_{10} + \beta_{11}PDI_i + \boldsymbol{\beta_{1CV}CV_i}$$

$$ln\left[\frac{\Pr(Y_i=TOP)}{\Pr(Y_i=DPJ)}\right] = \beta_{20} + \beta_{21}PDI_i + \boldsymbol{\beta_{2CV}CV_i}$$

$$ln\left[\frac{\Pr(Y_i=CP)}{\Pr(Y_i=DPJ)}\right] = \beta_{30} + \beta_{31}PDI_i + \boldsymbol{\beta_{3CV}CV_i}$$

$$ln\left[\frac{\Pr(Y_i=NS)}{\Pr(Y_i=DPJ)}\right] = \beta_{40} + \beta_{41}PDI_i + \boldsymbol{\beta_{4CV}CV_i} \quad (5.1)$$

Because the DPJ was the incumbent party when the disaster occurred, through comparing the effect on the party support for the DPJ and other parties, which party is more likely to be supported after the disaster can be understood. Therefore, in these equations, the probability of support for the DPJ is set as the referencing category, and it is represented as $\Pr(Y_i = DPJ)$ in equation (1). Additionally, $\Pr(Y_i = LDP)$ represents the probability of support for the LDP; $\Pr(Y_i = TOP)$ is the probability of support for the traditional opposition parties; $\Pr(Y_i = CP)$ expresses the probability of support for the challenger parties, and $\Pr(Y_i = NS)$ is no party support. The β_{j0} in equation (1) represents the constant of each equation. PDI_i and $\boldsymbol{CV}$ represent the perceived disaster impact and the vector of control variables, and β_{j1} and $\boldsymbol{\beta_{jCV}}$ are their regression coefficients. ε_{ji} expresses the error term in each equation.

Furthermore, to totally know which party or category is more likely to be supported, an additional marginal effect of perceived disaster impact in each of the models is calculated to compare them among the supports for the party or category.

At the prefectural level, the fixed-effect model is applied to the analyses, and it can be expressed as follows:

$$\Delta VS_{it} = \beta_1\Delta DI_{it} + \boldsymbol{\beta_{CV}}\Delta\boldsymbol{CV_{it}} + \beta_2\Delta T_i + \Delta\varepsilon_{it} \quad (5.2)$$

Just as in the equation in Chapter 3, in this analysis, ΔVS_{it} represents the voting share of each party; DI_{it} equals the disaster impact, and $\boldsymbol{CV_{it}}$ is the vector of the control variables; $\Delta\beta_1$ and $\Delta\boldsymbol{\beta_{CV}}$ represent the regression coefficients of DI_{it} and $\boldsymbol{CV_{it}}$. T_i is prefecture-specific fixed effects. $\Delta\varepsilon_{it}$ expresses the error term, including time t and individual i.

5.4 Results

Because the datasets are used at two levels, the results are also shown in two parts.

5.4.1 Results at the Individual Level

For the analyses at the individual level, the results are shown in Table 5.3.

Table 5.3 Results of Opposition Party Support at Individual Level

VARIABLES	Model 1 LDP	Model 2 TOP	Model 3 CP	Model 4 Nonsupport
Perceived disaster impact	0.285*	−0.228	0.159	0.0405
	(0.136)	(0.190)	(0.148)	(0.111)
Sex (Ref: Female)	−0.734**	−1.396***	−0.264	−1.358***
	(0.286)	(0.373)	(0.315)	(0.238)
Age	−0.000969	0.0148	−0.00468	−0.0102
	(0.0111)	(0.0149)	(0.0119)	(0.00907)
Education	−0.0672	−0.0697	0.000709	−0.0871
	(0.144)	(0.196)	(0.156)	(0.118)
Marriage (Ref: Non-married)	−0.563+	−0.670+	−0.779*	−0.673**
	(0.315)	(0.407)	(0.332)	(0.261)
Employment status (Ref: Management or Office)				
Regular employment	0.0883	1.025+	0.284	0.211
	(0.350)	(0.611)	(0.379)	(0.281)
Non-regular employment	−0.141	−0.311	−0.134	−0.615+
	(0.428)	(0.735)	(0.474)	(0.352)
Self-employment or family employment	0.281	0.0697	0.384	0.0817
	(0.455)	(0.804)	(0.490)	(0.379)
Unemployment	−0.0328	0.0615	−0.180	−0.414
	(0.391)	(0.665)	(0.435)	(0.321)
Individual income (Log)	0.116	−0.537*	−0.324	−0.279+

	(0.207)	(0.261)	(0.215)	(0.167)
TV watching	−0.109	−0.239	0.0253	−0.100
	(0.131)	(0.159)	(0.145)	(0.109)
Newspaper reading	−0.0193	−0.0148	0.0564	−0.0356
	(0.0809)	(0.109)	(0.0885)	(0.0658)
Internet usage	0.0622	0.00272	0.0913	−0.00469
	(0.0706)	(0.0979)	(0.0765)	(0.0580)
Constant	−0.0852	4.596*	1.498	5.788***
	(1.751)	(2.231)	(1.855)	(1.419)
Observations		1141		
G^2		115.610***		
Nagelkerke R^2		0.106		

Standard errors in parentheses

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, * $p < 0.1$

Because the reference category of the dependent variable is DPJ, these results show the comparison of the effect of perceived disaster impact on the support for the DPJ and other parties. Model 1 in Table 5.3 shows the comparison between DPJ and LDP, and the results suggest that the perceived disaster impact is positively and significantly associated with the dependent variable. Thus, compared with supporting the DPJ, people who were affected in the disaster are more likely to support the LDP. The regression coefficient of perceived disaster impact is 0.285, and the odds ratio is 1.330, which means people were affected by the disaster in 1 scale, and the probability of supporting the LDP is 1.33 times bigger than supporting the DPJ. In the other models in Table 5.2, all the coefficients of perceived disaster impact are nonsignificant. Thus, the degree of perceived disaster impact has no effect on the support of these parties compared with the support for the DPJ. According to these results, disaster-affected people are more likely to support the LDP rather than other parties. However, this model is only the model that set DPJ as the reference category. The general results of the support for these parties are unknown, and an assessment must be conducted through marginal effect analyses.

The results of the marginal effect are presented in Table 5.4.

Table 5.4 Marginal Effect of Perceived Disaster Impact

Marginal effect on the Probability of	Average marginal effect of perceived disaster impact
DPJ	−0.013
	(0.013)
LDP	0.032*
	(0.013)
Traditional opposition Parties	−0.015+
	(0.008)
Challenger parties	0.010
	(0.011)
Non-party support	−0.013
	(0.018)

Delta-mentioned standard errors in parentheses

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

The results in Table 5.4 show that perceived disaster impact has a significant and positive effect only on the support of the LDP. Additionally, generally, the disaster effect improves the support of LDP. The results also show that perceived disaster impact is negatively and significantly associated with the support of traditional opposition parties. This outcome is not presented in Table 5.2 and means that generally, perceived disaster impact has a negative effect on, or in other words, reduces the support for, traditional opposition parties. Furthermore, Table 5.4 confirms that perceived disaster impact will not influence the support for the ruling party—the DPJ—because the marginal effect on the support for the DPJ is nonsignificant. This finding is a little different from the findings in the literature.

Figure 5.1 presents the results in Table 5.3

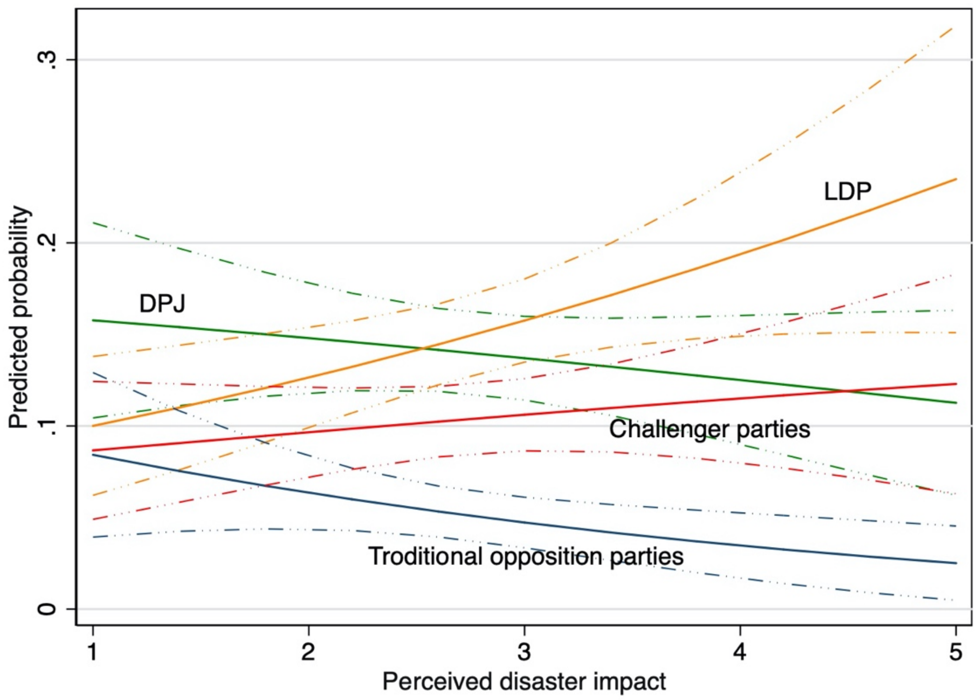

Figure 5.1 Results of Marginal Effects

The orange lines represent the trend of the support for the LDP; green lines are the DPJ; red lines are the challenger parties, and navy lines are the traditional opposition parties. Because this study does not focus on party support, Figure 5.1 did not include it. The following is also confirmed: the slope of the LDP is the biggest, meaning that the perceived disaster impact will improve the support of the LDP. For the support of the challenger parties, although the trend is increasing, it is not significant (Table 5.3).

5.4.2 Results at Prefectural Level

At the prefectural level, because from 2004 to 2015 there are two parties, the LDP (2004–2009 and 2012–2015) and the DPJ (2009–2012) were elected as the ruling party, and the results are shown in two parts based on these two periods. In Chapter 2, because the literature mentioned that disasters can allow people to dismiss the incumbent party through support for opposition parties, the effect of disasters on the support for opposition parties is through the influence of the support for the incumbent party. In other words, the support for the incumbent party may mediate the influence of disasters on the support for opposition parties. Therefore, the voting share of the ruling party is included in the analyses of the voting share of opposition parties.

The first part showed the results in the period when the DPJ was the ruling party (Table 5.5).

Table 5.5 Results of the Vote Share at the Prefectural Level (DPJ is Ruling Party)

	Model 1	Model 2	Model 3	Model 4
VARIABLES	DPJ	LDP	TOP	CP
Disaster impact	−0.0707	−0.0457	−0.0121	−0.0631
	(0.0754)	(0.0412)	(0.0396)	(0.192)
DPJ voting share		−0.0643	−0.471***	−1.154
		(0.143)	(0.145)	(0.925)
Population density (log)	−110.8*	19.22	−19.50	−79.30
	(64.40)	(62.02)	(56.11)	(321.3)
Women proportion	−493.8	690.9	−244.5	−3,604
	(525.6)	(580.8)	(464.0)	(3,580)
Elderly proportion	−291.5*	217.3	−245.5*	−8.724
	(171.4)	(155.9)	(124.9)	(1,101)
Employment rate	24.66	−85.13	80.99	−244.6
	(82.02)	(72.17)	(65.20)	(508.6)
GDP per capita	0.00340	0.00168	0.00693*	0.0217
	(0.00499)	(0.00273)	(0.00362)	(0.0149)
Disaster recovery expenditure rate	−100.6***	−17.57	−44.61*	−215.8
	(21.52)	(17.36)	(22.22)	(154.8)
Vote rate	−0.141	−0.319	0.178	−0.566
	(0.183)	(0.203)	(0.171)	(1.313)
Election type (Ref: house of representative)	−9.152***	3.954	−6.236**	−13.51
	(2.332)	(2.754)	(2.794)	(20.36)
Proportion of challenger party	−0.404	−1.607	5.756***	33.89***
	(1.591)	(1.032)	(1.057)	(5.100)
Constant	−290.9	−220.1	22.41	1,527
	(551.7)	(506.2)	(496.7)	(3,097)
Observations	94	94	94	94
R^2	0.967	0.686	0.486	0.341
Number of prefectures	47	47	47	47
Within R^2	0.967	0.686	0.486	0.341
Between R^2	0.0579	0.0709	0.0381	0.00778
Overall R^2	0.0234	0.0417	0.0167	0.0113
Year effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1

The results suggest that disaster impact has no influence on the voting share of all the parties or categories because its coefficients in all the models are nonsignificant. The result of the DPJ is the same as in Table 5.3, and the result of the LDP is a little different from that in Table 5.3. The difference may be caused by the small sample size in the analysis; therefore, it is necessary to read the result compared with the results at the individual level.

The second part showed the results in the period when the LDP was the ruling party (Table 5.6).

Table 5.6 Results of the Vote Share at the Prefectural Level (LDP is Ruling Party)

	Model 5	Model 6	Model 7	Model 8
VARIABLES	LDP	DPJ	TOP	CP
Disaster impact	−0.0272**	0.0222*	0.0141	−0.0335
	(0.0122)	(0.0119)	(0.0489)	(0.0488)
LDP voting share		−0.214**	−0.0273	0.0237
		(0.0801)	(0.101)	(0.159)
Population density (log)	−55.91***	−30.05**	7.116	26.46
	(12.70)	(14.67)	(13.03)	(36.20)
Women proportion	60.81	−254.7	217.6	652.2
	(301.2)	(225.8)	(194.0)	(593.0)
Elderly proportion	−40.92	−102.7**	−2.588	103.0
	(46.19)	(44.36)	(36.09)	(88.62)
Employment rate	4.909	11.26	13.72	−13.40
	(27.30)	(23.63)	(20.91)	(69.30)
GDP per capita	−0.000331	−0.000954	0.00138	0.00771
	(0.00164)	(0.00180)	(0.00126)	(0.00552)
Disaster recovery expenditure rate	−7.563	−56.17***	13.61	80.61**
	(7.272)	(20.59)	(19.69)	(32.82)
Vote rate	0.0178	−0.107	−0.0724	−0.623**
	(0.136)	(0.151)	(0.102)	(0.300)
Election type (Ref: house of representative)	7.193***	13.72***	−1.791	15.82**
	(1.600)	(4.185)	(2.394)	(7.660)
Proportion of challenger party	−0.346	0.594	5.262***	32.58***

	(0.604)	(0.625)	(0.705)	(1.716)
Constant	−313.9*	12.75	−67.87	−203.1
	(185.1)	(166.9)	(144.1)	(438.9)
Observations	235	235	235	235
R^2	0.786	0.963	0.403	0.638
Number of prefectures	47	47	47	47
Within R^2	0.786	0.963	0.403	0.638
Between R^2	0.0681	0.0430	0.0244	0.0168
Overall R^2	0.0509	0.167	0.0584	0.0270
Year effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Table 5.6, Model 5 shows the results of the voting share for the DPJ. The variable of disaster impact is positively and significantly associated with the dependent variable, meaning that a disaster will help to promote party support for the DPJ when the LDP is the ruling party. In Model 6, the coefficient of disaster impact is significantly negative, which means that a disaster will decrease the support for LDP when it is the ruling party. In other words, voters will punish the LDP when affecting natural disasters. Models 7 and 8 show the results of traditional opposition parties and challenger parties. The coefficients of disaster impact are nonsignificant. Thus, when the LDP was the ruling party, the natural disasters had no influence on the support of both traditional opposition parties and challenger parties.

Additionally, because the LDP has a period as the ruling party, the disasters may have a long-term effect on the voting share of the parties when the ruling party is the LDP. To demonstrate this point, an additional analysis including the time lag of disaster impact in three years is conducted, and the results are shown in Table 5.7.

Table 5.7 Results of the Vote Share at the Prefectural Level (LDP is Ruling Party and with time lag)

	Model 9	Model 10	Model 11	Model 12
VARIABLES	LDP	DPJ	TOP	CP
Disaster impact	−0.0288**	0.0295**	0.0224	−0.0128
	(0.0123)	(0.0130)	(0.0410)	(0.0347)
Disaster impact (t−1)	−0.00246	0.0166***	0.0175	0.0350
	(0.00467)	(0.00576)	(0.0141)	(0.0220)
Disaster impact (t−2)	−0.000399	0.000543	−0.00244*	−0.000271
	(0.000615)	(0.001000)	(0.00134)	(0.00240)
Disaster impact (t−3)	0.000361	0.00219*	−0.00221	−0.00583***
	(0.000836)	(0.00116)	(0.00160)	(0.00207)
LDP voting share		−0.211**	−0.0217	0.0427
		(0.0808)	(0.0986)	(0.165)
Population density (log)	−56.23***	−33.10**	12.00	36.22
	(13.41)	(13.74)	(13.44)	(38.11)
Women proportion	78.11	−309.9	39.19	322.9
	(318.4)	(240.6)	(212.2)	(671.7)
Elderly proportion	−40.09	−106.0**	−6.548	93.53
	(46.15)	(44.54)	(33.08)	(88.91)
Employment rate	5.487	9.604	1.801	−31.78
	(27.90)	(23.80)	(20.78)	(74.09)
GDP per capita	−0.000389	−0.00116	0.00196	0.00889
	(0.00171)	(0.00179)	(0.00135)	(0.00551)
Disaster recovery expenditure rate	−5.744	−72.37***	8.625	65.60***
	(8.349)	(16.56)	(12.84)	(20.76)
Vote rate	0.0170	−0.0966	−0.0525	−0.596*
	(0.138)	(0.156)	(0.106)	(0.303)
Election type (Ref: house of representative)	7.229***	−6.373**	0.765	8.683
	(1.635)	(2.565)	(1.525)	(6.169)
Proportion of challenger party	−0.305	0.593	5.182***	32.19***
	(0.614)	(0.617)	(0.768)	(1.732)
Constant	−324.9	45.15	52.65	34.18
	(198.9)	(168.5)	(158.9)	(482.2)

Observations	235	235	235	235
R^2	0.787	0.964	0.426	0.649
Number of prefectures	47	47	47	47
Within R^2	0.787	0.964	0.426	0.649
Between R^2	0.0681	0.0432	0.0210	0.0163
Overall R^2	0.0507	0.145	0.0320	0.0101
Ruling party (t−1, 2, 3)	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

There are four models in Table 5.6, and they represent the results of the voting share of the LDP, DPJ, traditional opposition parties, and challenger parties, respectively. For the voting share of the LDP, which is the ruling party in this period, the results suggest that only the disasters in this year have a significantly negative effect on its voting share, and there is no effect in other years. Thus, natural disasters reduce the voting share only in the short term. The results of the DPJ in Model 10 indicate that the disaster impacts the year the disaster occurred, and one year before and three years before all have a significantly positive effect on its voting share. These outcomes suggest that the disasters promote the DPJ's voting rate both in the short and long term when it is not a ruling party. Model 11 shows the results of traditional opposition parties, and the disaster at two years before has a significantly negative effect on its voting share. This finding means that in the long term, the disasters reduce the support for the traditional opposition parties. These results are the same as the results of traditional opposition parties, and the results of the challenger parties in Model 12 also show that the disasters at three years before have a significantly negative effect on their voting share. This outcome means that the disasters also reduce the support for traditional opposition parties in the long term. Based on these results, the disasters only promote support for the DPJ in both the short term and long term when the LDP is ruling party.

5.5 Conclusion

In this chapter, two contrary theories that describe how the disasters impact the support for opposition parties are empirically demonstrated through two sets of data at both individual and prefectural levels. Through the multinomial logistic regression at the individual level and fixed-effect model at the prefectural level, this study yielded two main findings. First, when the DPJ was the ruling party, people were less likely to punish it when affected by natural disasters, and when the LDP was the ruling party, people were more likely to punish it. Second, people, at least in Japan, affected by the disasters have a higher probability of supporting the parties that have more power and experience in managing economic growth or welfare rather than supporting the challenger parties.

The first finding differs from our predictions. Because of the Great East Japan earthquake and tsunami, because of the late response of the ruling party, the Japanese people were dissatisfied with the DPJ and were more likely to punish this party in the following election. However, the results at individual and prefectural levels suggest that people did not punish the DPJ when affected by the disasters. By contrast, the LDP, the most experienced party, was punished by the voters when affected by the disasters. To discuss this problem, additional research is required.

The results at individual and prefectural levels indicate that people affected by disasters will support the issue-salient party rather than the challenger party. This finding is inconsistent with the results of the economic crises in European countries, which was concluded as economic theory. It provides empirical evidence that proves that issue owner theory is appropriate when explaining how disasters influence the support for opposition parties.

CHAPTER 6
Conclusion and Discussion

Studies concerning the impacts of natural disasters on sociopsychological, economic, and political aspects have provided abundant empirical evidence for the theories proposed by early disaster research; however, several empirical blanks or disadvantages remain. The studies on sociopsychological aspect only concentrated on the impact of natural disasters on the attitudes and behaviors of ingroups (e.g., Barton 1969; Calo-Blanco et al. 2017; Chang 2010; Fritz 1961; Lee and Freser 2019; Prelog 2016; Solnit 2009), and none of them have investigated the attitudes and behaviors among the intergroup. Concerning the economic perspective, researchers have explored the impact on income inequality at the macrolevel (e.g., Fang et al. 2017; Guimaraes et al. 1993 Shaughnessy et al. 2010); however, none have demonstrated the mechanism assumed in these studies at the individual level. Regarding the political aspect, researchers have estimated the disaster impact on the support for the incumbent party (e.g., Cole et al. 2012; Gasper and Reeves 2011; Healy and Malhotra 2009, 2010), and none have attempted to investigate how disasters impact the support for opposition parties. The primary goal of this dissertation is to provide empirical evidence for the aforementioned empirical blanks or disadvantages. This study uses Japan as an example and obtains several main findings as follows: first, disaster impacts decrease the discrimination against foreigners in the short term after large-scale disasters; second, disasters promote income inequality through a different influence on regular and non-regular employees; finally, disasters promote support for the most powerful and experienced opposition party.

For the relationship between disaster impacts and discrimination against foreigners, the results provided evidence to support the theory of common ingroup identity. However, the additional results showed that disasters only affect discrimination against foreigners in the short term and in large-scale disasters. Two reasons may help explain these findings. The first reason is the effect of large-scale disasters, and the problem is with the analytic level. Because this study used the dataset at the prefectural level for analyses, the case of discrimination is also collected at the prefectural level. In this sense, small-scale disasters, which only affect a small area in the prefectures, may not influence discrimination at the prefectural level. Therefore, only large-scale disasters that influence the whole prefecture will alter discrimination against foreigners. This reason implies that the analyses at a smaller level should be conducted to explore more detailed facets of the influence. The second reason regards the short-term effect. According to the common ingroup identity model, people decategorize themselves from the original categories affected by disasters. However, after disasters, native people and foreigners recover their normal lives, and the attitudes between these two groups may also return to what was observed before. Therefore, disasters do not have a long-term effect on the attitudes and behaviors between these two groups.

Concerning the results on income inequality, as mentioned in Chapter 4, compared with regularly employed workers before the disaster, non-regularly employed workers are more likely to lose the job in the disaster. This finding is consistent with social vulnerability theory. Notably, the results of disaster impact on employment status after disaster are completely consistent with the research conducted by Genda (2014), which used the data of the Employment Structure Survey in 2012. However, this research did not sequentially demonstrate the impact of the disaster on individual income between regularly and non-regularly employed workers.

In the long term, non-regularly employed workers can return to the same employment status easier than regularly employed workers; thus, they are less likely to have a lower wage than before, compared with regularly employed workers. Through this approach, although the average income between regularly employed and non-regularly employed workers will decrease, because in the whole society people with lower socioeconomic status additionally increased, general income inequality should increase after the disaster. Therefore, both in the short term and long term, income inequality is promoted by the disasters. These results provide evidence that disasters may increase income inequality from the individual level.

The results regarding the relationship between disaster impacts on support for opposition parties showed that people are more likely to support parties with salient issues concerning economic growth and welfare rather than challenger parties. These results provided empirical evidence that supports issue owner theory, which indicates that experienced parties will be supported when the issues become salient. However, the results also suggested that when facing disasters, people will punish the LDP rather than the DPJ when these two parties were the ruling party, separately. As mentioned in Chapter 5, this result differs from our predictions that the DPJ is more likely to be punished than the LDP. One reason may help to explain this result, that is, the different policies provided by these two parties. According to the literature, people affected by disasters will support the parties that provide expectations of future distribution of welfare, because they concentrate on the expected benefits they will receive (Visconti 2018). Because the DPJ provides more policies concerning welfare than the LDP, people may be dissatisfied with the disaster management of the DPJ will not punish it based on the disaster impact.

This empirical study contributes to the literature on the natural disaster impact on societies in three ways. First, this study represents the first to attempt to systematically explore the impact of disasters on the behaviors from the ingroup to the outgroup. According to the results, disasters reduce negative behaviors, such as discrimination, from native people against foreigners. Additionally, because the literature mentioned that disasters may result in a better society, combined with the results of this study, I propose that a disaster creates a therapeutic community within society. Through this approach, the theory of disaster affects the sociopsychological aspect and becomes more perfect according to this study.

Second, this study is the first to individual-level data to demonstrate the mechanism that explains the impact of disasters on income inequality. These results allow us to explore more details of the relationships among disaster impact, employment status, and individual income. Before this study, governments or scholars only paid attention to the poor people who were defined as the vulnerable group. This study suggests that not only poor people are affected by disasters; people who have a relatively higher socioeconomic status may also be affected by disasters. Thus, we should also pay attention to this group.

Finally, compared with the literature, this study is the first attempt to explore the impact of disasters on the support of opposition parties. The results supported issue owner theory and suggested that people affected by the disasters are more likely to support the opposition parties with salient issues of economic growth and welfare. This finding is critical because disasters may result in the replacement of the incumbent government. For the citizens and scholars, which party is the next ruling party will alter the prediction of social development in the following period.

This study has limitations. First, for the analyses of discrimination, because the data used is collected at the prefectural level, only the large scale will have a significant effect on the discrimination against foreigners. Further research should analyze the data at a relatively small-scale. Second, the sample size of unemployed workers affected by the disaster is relatively small. This disadvantage causes omitted coefficients in the analyses. To check the robustness, further research should use a bigger sample size of unemployed workers affected by the disaster. Finally, the sample size of the prefectures in the period when the ruling party was the DPJ is small. Thus, further research should use data collected in a longer period.

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